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UNIVERSITY OF THE WITWATERSRAND, JOHANNESBURG

FACULTY OF COMMERCE, LAW AND MANAGEMENT

AN IN-DEPTH VALIDATION OF MOMENTUM AS A DOMINANT EXPLANATORY FACTOR ON THE JOHANNESBURG STOCK EXCHANGE

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A thesis submitted to the Faculty of Commerce, Law and Management, University of the Witwatersrand, in fulfilment of the requirements for the degree of Doctor of Philosophy (Ph.D).

Johannesburg, South Africa

September 2016

DECLARATION

I, Moshe Daniel Page, declare that this research report is my own unaided work. It is submitted in full fulfilment of the requirements for the degree of Doctor of Philosophy (PhD) in Finance at the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination in this or any other university.

ACKNOWLEDGEMENTS

I owe a huge debt of gratitude to my supervisor and mentor, Professor Christo Auret who has inspired and guided me on this journey and provided me with one of the greatest gifts one person can bestow on another, self-belief. No words could ever express the indebtedness I feel towards you, specifically for awakening within me with the will to succeed and a passion and love for the fields of corporate finance and investment. I am truly grateful to my parents and siblings, whom have always shown love and support. Most importantly, I am hugely grateful to my wonderful wife Carri, who has been a pillar of strength, kindness and source of devotion for me in completing this study. Lastly, I feel completely blessed to have been able to submit my PhD just prior to the arrival of my first born son, Benjamin Noah, who I love more than life itself.

Daniel Page

September 2016

GLOSSARY OF TERMS

J203 ALSI	*JSE All-share index*
Alpha	*Intercept term of the linear regression*
AMEX	*American Stock Exchange*
APT	*Arbitrage Pricing Theory*
Beta	*Either the slope coefficient of the OLS regression or the CAPM beta*
BM	*Book-to-market ratio (Book value per share scaled by market price per share)*
CAPM	*Capital Asset Pricing Model*
CRSP	*Center of Research in Security Prices*
CFP	*Cash flow-to-price (Cash flow per share scaled by market price per share)*
EMH	*Efficient Market Hypothesis*
EMRP	*Equity market risk premium*
Error	*Residual term of the OLS regression*
FINDI	*JSE Financial and Industrial Index*
Idiosyncratic risk	*Measure of firm specific risk interchangeable with volatility*
JSE	*Johannesburg Stock Exchange*
Market Capitalization	*Price per share multiplied by number of shares in issue*
NASDAQ	*National Association of Securities Dealers Automated Quotations*
NYSE	*New York Stock Exchange*
OLS	*Ordinary Least Squared Regression*
P/E	*Price/Earnings ratio (Price scaled by earnings per share)*
RESI	*JSE Resources Index*
Risk-free rate	*Prevailing risk-free rate generally proxied by the 90 day Treasury*
Turnover	*Trading Volume scaled by number of shares in issue*
ZAR	*Shorthand for the Rand exchange rate*

AN IN-DEPTH VALIDATION OF MOMENTUM AS A DOMINANT EXPLANATORY FACTOR ON THE JOHANNESBURG STOCK EXCHANGE

ABSTRACT

This study considers momentum in share prices, per Jegadeesh and Titman (1993, 2001), on the cross-section of shares listed on the JSE. The key research objective is to define whether momentum is significant, independent and priced. 'Significant' implies that momentum produces significantly positive nominal and risk-adjusted profits, 'independent' means that momentum is independent of other non-momentum stylistic factor premiums and finally, 'priced' suggests that momentum is a priced factor on the JSE and thereby contributes to the cross-sectional variation in share returns. In order to determine the significance of the momentum premium on the JSE, univariate momentum sorts are conducted that consider variation in portfolio estimation and holding periods, weighting methodologies as well as liquidity constraints, price impact and micro-structure effects. The results of the univariate sorts clearly indicate that momentum on the JSE is both significant and profitable assuming estimation and holding periods between three and twelve months. Furthermore, consistent with international and local literature, momentum profits reverse assuming holding periods in excess of 24 months. In order to determine whether momentum is independent, bivariate sorts and time-series attribution regressions are conducted using momentum and six non-momentum factors, namely: Size, Value, Liquidity, Market Beta, Idiosyncratic Risk and Currency Risk. The results of the bivariate sorts and time-series attribution regressions clearly indicate that momentum on the JSE is largely independent of the non-momentum stylistic factors considered. Lastly, cross-sectional panel regressions are conducted where momentum is applied, in conjunction with the considered non-momentum factors, as an independent variable in order assess the relationship between the factors and expected returns on a share-by-share basis. The results of the panel data cross-sectional regressions clearly indicate that momentum produces a consistently significant and independent premium, conclusively proving that momentum is a priced factor that contributes to the cross-sectional variation in share returns listed on the JSE.

Keywords**:** *Momentum, factor pricing, premium, cross-section*

JEL Classification: C10; C12; C58; G10; G11; G12

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CHAPTER ONE: INTRODUCTION

1.1 INTRODUCTION

Momentum in share prices, accredited to the seminal research by Jegadeesh and Titman (1993), is a stylistic trading anomaly that entails investing in shares based on their recent return performance. The term 'momentum' relates to relying on the current or short term trajectory of a shares' respective returns, assuming that the positive (negative) historical 'momentum' will continue to produce positive (negative) returns over the future short to medium investment period. Post the work of Jegadeesh and Titman (1993), a plethora of studies across a range of geographies and asset classes have found that momentum strategies almost always produce significant positive excess returns that cannot be explained by conventional risk-based pricing theories and their model manifestations. Fama and French (1998) stated that momentum is the single biggest stumbling block to the efficient market hypothesis as their three factor model, made up of a market risk, size and value premium, failed to explain the significant profits earned through momentum strategies.

Momentum as a trading anomaly can be traced to the study of long-term reversal accredited to De Bondt and Thaler (1985, 1987), where the authors found extreme reversal in historical winner and loser share performance over 'long' holding periods, typically between 12 and 60 months. A number of studies (see De Bondt and Thaler (1985,1987), Chan, Jegadeesh and Lakonishok (1996), Barberis, Shliefer and Vishny (1998) and Daniel, Hirshleifer and Subrahmanyam (1998)) have credited the presence of reversal to overreaction, where market participants initially 'overreact' to positive or negative news, driving price levels beyond their intrinsic 'true' values. Momentum, by nature and design, focuses on shorter investment horizons and therefore takes advantage of the positive (negative) 'momentum' in winner (loser) shares prior to the effect of mean reversion or 'reversal' being experienced. Uniquely, the presence of momentum presents a conundrum as unlike size and value, momentum is not easily explained using a risk-based framework. The simultaneous lack of sufficient evidence and theoretically appealing risk based explanations led to adoption of psychological models or behavioural finance that rely on the irrational nature of market participants to explain the existence of momentum over short investment horizons (between three and 12 months) and eventual reversal thereafter.

A key objective of this study is the determination of whether momentum on the JSE is a priced factor. In order to achieve the key objective, the study requires the examination of whether momentum produces significant univariate excess returns, is significantly independent when combined with other pricing anomalies and lastly, evaluate whether the momentum is priced factor that explains the cross-sectional variation in share returns. The facets to be explored, as described above, can be directly related to the two key empirical sub-fields of financial economics,

namely corporate finance and investment. Investment, in this context relates to buy-side asset management, equity research and fund risk analysis. The determination of investment strategies that produce excess returns or relatively high levels of alpha that are uncorrelated with other factor anomalies are of paramount importance to investment practitioners. Beyond the determination of relatively profitable investment strategies, the development of attribution models that allow for the accurate determination of alpha and manager skill is highly beneficial to industry. Therefore, the definition of the optimal univariate momentum strategy, bivariate combination momentum strategy (momentum and non-momentum pricing anomalies considered), the independence of momentum on the JSE and defining whether momentum is an appropriate independent variable to be incorporated within a factor attribution model are all vital and significant to local and international asset managers, risk analysts and private investors.

Corporate finance, which relates to the fields of valuations, due diligence and private equity can benefit through the determination of a true multi-factor asset-pricing model appropriate to the JSE. Numerous South African studies have found that the capital asset pricing model ("CAPM" hereafter) fails to describe the risk-return relationship on the JSE, specifically when utilizing the JSE All-share index ("JSE ALSI" or "J203" hereafter) as the market proxy. Given the surplus of evidence against the adequacy of the CAPM, the majority of corporate finance practitioners still apply some form of the CAPM[1]. The development of an unbiased and statistically precise multifactor model would be highly beneficial to key players within industry in determining accurate discount rates (both cost of equity and weighted average cost of capital) to be applied in valuations and determination of appropriate hurdle rates.

Academically, the presence of momentum on the JSE is further evidence against the capital asset pricing model describing the risk-return relationship, allowing for the analysis and development of arbitrage pricing theory ("APT" hereafter) risk premia based models that provide a superior description of the 'risk/expected return' relationship appropriate to the South African stock market. Moreover, the lack of a sufficient risk based explanation would imply that momentum on the JSE is possibly driven by behavioural finance theories, suggesting that the JSE and its market constituents display behavioural qualities that have been found globally in both developed and developing stock exchanges. Lastly, the current body of South African literature on the momentum anomaly is relatively sparse when compared to the likes of the small size anomaly and value premium. Therefore, an in-depth examination of the momentum anomaly will add significantly to the current body of knowledge related to financial economics, investments and asset pricing and provide additional avenues for further research in the aforementioned fields.

[1] PWC Valuation Survey 2014/2015 indicates that 83% of practitioners apply the CAPM in order to define a risk-adjusted cost of equity

The paragraphs above allude to the intentions of this study, which are four-fold. Initially, the study intends to uncover the optimal univariate momentum strategy on the cross-section of shares listed on the JSE, considering a number of empirical permutations including variations in the historical estimation period, portfolio holding period, liquidity and price impact constraints. The univariate analysis will also test for the effects of short-term and long-term reversal, as described by Debondt and Thaler (1985, 1987), entailing the testing of whether skipping a single month between the estimation and holding period and extending portfolio holding periods in excess of year results in historical winner portfolios underperforming their loser counterparts. The results of the univariate analysis will provide the base argument of the study, defining whether under various portfolio estimation and holding periods, momentum is present and significant on the cross-section of shares listed on the JSE utilizing virtually identical tests applied by Jegadeesh and Titman (1993, 2001). The results of the univariate tests will substantially add to the current body of knowledge and South African literature on the subject.

The second aspect of the study intends to determine whether momentum is explained by other factor pricing anomalies considered in literature. Bivariate dependent and independent sorts are to be conducted where shares are sorted simultaneously on momentum and one of the six non-momentum investment styles considered within the study, namely; size proxied by market capitalization, value proxied by the book-to-market ratio, liquidity proxied by the turnover ratio, liquidity adjusted market beta, idiosyncratic risk and currency or ZAR beta. The bivariate tests intend to describe the independence of momentum on the JSE as well as its comovement (interaction) with other popularized investment styles. The results of the bivariate sorts will significantly extend the current body of South African literature, considering unexplored pricing anomalies and their relationship with momentum.

The study then extends the examination of the momentum anomaly to a multivariate setting, testing whether the non-momentum styles in the form of excess return premiums are able to explain momentum profits using time-series attribution regressions. The various momentum portfolio alphas and factor weightings are analyzed in order to determine whether the predefined factor models explain the momentum premium. In addition, portfolio alphas are jointly tested using the Gibbons, Ross and Shanken (1989) test statistic (“GRS” or “GRS test statistic” hereafter) in order to determine whether the ex-ante defined pricing factors jointly explain the momentum premium. The null of GRS statistic is that the underlying pricing model explains the variation in portfolio returns by reducing portfolio alphas to be jointly equivalent to zero. The results of both the bivariate sorts and multivariate attribution regressions will provide new and further insight into the independence and risk-adjusted (factor adjusted) profit achieved by momentum strategies on the JSE.

The final penultimate test will take the form of a further multivariate regression, yet momentum now takes the form of an explanatory independent variable as opposed to the dependent variable. The natural logical progression dictates that if momentum is present, independent and consistent on the JSE, to what extent does it contribute to the cross-sectional variation in share returns? The final set of tests will define which of the priced factors considered in both the bivariate sorts and attribution regressions are significant determinants of the cross-sectional variation in share returns on the JSE. The core purpose of the test centers around momentum and its significance in explaining expected returns in conjunction with other priced factors considered. Primarily, if momentum produces significantly positive coefficients throughout the cross-sectional regression analysis, one can conclude that momentum is an essential explanatory variable that drives variation in share returns on the JSE. Additionally, the cross-sectional regression analysis will also offer specific insight into the range of explanatory variables that describe share returns on the JSE, thereby defining an appropriate factor pricing model for the JSE, extending the work of van Rensburg and Robertson (2003), Basiewicz and Auret (2009, 2010), Hodnett, Hsieh and van Rensburg (2012) and Ward and Muller (2013).

As described, the benefits of the results extend to both practitioners and academics alike by considering variations in empirical techniques applied to asset pricing tests (cross-sectional panel data models), unexplored factors such as momentum, liquidity, market beta, idiosyncratic risk and currency beta and most importantly, defining the principal components that govern the data generating process for share returns on the JSE. Notably, the study is of an empirical nature and therefore intends to answer a number of research questions related to the presence of momentum on the JSE, its resilience and consistency when considered in a multivariate framework, and lastly, the degree to which momentum explains cross-sectional variation of share returns on the JSE. The study uses techniques that are specifically applied to risk based analyses of pricing factors yet, the core essence of the study does not question whether risk or behavioral framework best describe the momentum premium, but rather whether momentum is a priced factor on the JSE that contributes to the cross-sectional variation in share returns.

1.1 BACKGROUND OF THE PROBLEM

Prior to presenting an in-depth coverage of the current body of local and international literature (which is to be presented in Chapter Two), a brief description of key literature is presented in order to develop the necessary background to contextualise the problem statement. Jegadeesh and Titman (1993) is considered the formative study into the concept of underreaction and momentum in share prices over medium term holding periods. Momentum as an investment style was however previously considered in prior literature, albeit under a different name. Levy (1967) considered a momentum strategy (referred to as a relative strength strategy) that bought shares with prices that were higher than their prior 27 week average and found that such a trading rule

achieved profits in excess of a buy-and-hold strategy. Jensen and Bennington (1970) applied the same trading rule out of sample and found that the strategy did not beat a passive investment strategy, thereby attributing the original result to sample selection bias. Grinblatt and Titman (1992) found that the majority of mutual fund managers in the US tended to buy shares that had increased in value over the previous trading quarter.

Literature prior to Jegadeesh and Titman (1993) was largely focused on the overreaction hypothesis and the success of contrarian strategies in generating abnormal returns. The authors noted that the study of contrarian investment strategies were largely confined to either extremely short-term horizons i.e. between one week and one month or extremely long holding periods i.e. between 36 and 60 months. The novel approach used by Jegadeesh and Titman (1993) was to study the unexplored portfolio holding period of the medium term namely, 3 to 12 months. Importantly, the authors conducted separate tests on price momentum, relying solely on share prices as the informational driver necessary for developing an investment strategy.

Jegadeesh and Titman (1993) found that over the medium term, the profits attributable to momentum strategies were significantly positive. The authors used historical share performance over the previous *J* months, equivalent to 1, 2, 3 or 4 quarters, and held shares for an equivalent *K* months, where *K* would take on the identical periods as *J*, namely 1, 2, 3 or 4 quarters. Portfolios were constructed monthly allowing for the portfolios to overlap, increasing the amount of simulations conducted for each strategy. The authors further considered portfolio formations allowing for a single week period between share selection and portfolio formation in order to account for bid-ask bounce and micro-structure effects as expressed by Lehmann (1990). The authors found that all of the simulations resulted in positive excess returns with 31 out of 32 being significantly different from zero. In attempt to decompose the momentum profits achieved, the authors considered the *J*=6; *K*=6 month strategy and calculated the post-ranking market beta's (CAPM betas) in order to identify whether systematic risk was driving momentum profits.

The authors found that post-ranking betas for the extreme portfolios were significantly higher than the other decile portfolios and that the extreme loser portfolios produced greater market betas than their winner portfolio counterparts, implying that systematic risk was not driving excess returns. A further test of the source of momentum profits was conducted by exploring the average market capitalization of shares in each of the portfolios. The authors found that the extreme loser portfolios contained smaller shares on average implying that the size effect was not a contributor to momentum profits achieved. Jegadeesh and Titman (2001) extended their initial study to include the period 1990 – 1998 and increased the universe of shares to all shares listed on the NYSE, AMEX and NASDAQ over the sample period. Using a six month estimation and holding period (*J*=6; *K*=6), the authors found that the zero cost strategy yielded excess returns of 1.39% per month.

Grundy and Martin (2001) conducted a study of medium-term momentum on a cross-section of US shares (AMEX and NYSE) over the time period August 1926 to July 1995. The authors found that over the entire sample period, momentum strategies earned a risk-adjusted returns in excess of 1.3% per month. Fama and French (1996) conducted a study on momentum and whether a Fama-French Three factor model is able to explain medium term momentum profits using size and value as risk factors. The authors found that over the period July 1963 to December 1993, the cross-section of shares on the NYSE displayed significant momentum, with the best performing momentum portfolio achieving an excess return of 1.31% per month.

The most cited non-US international studies of medium term momentum are those of Rouwenhorst (1998, 1999), Chui, Titman and Wei (2000) and Griffin, Ji and Martin (2003, 2005). Rouwenhorst (1998) conducted a momentum study on international equity markets as all of the previous studies conducted on US markets utilized similar datasets (CRSP data) that considered similar time periods. Asness, Liew and Stevens (1997) studied return patterns across differing geographical markets, yet the study was conducted at the country index level and not on the individual stock level. Rouwenhorst (1998) considered individual stock prices with a total sample of 2190 shares across 12 European countries (exchanges) over the time period 1978 to 1995. The author found that momentum was present on the cross-section of European shares and that the zero cost strategy achieved excess average returns of approximately 1% per month across each of the 12 equity exchanges considered. Furthermore, consistent with previous literature, the author found that attempting to control for size and market risk actually increased the risk-adjusted performance of the momentum portfolios and that the return continuation lasted for approximately one year on average.

Rouwenhorst (1999) tested whether return factors (stylistic factors) such as value, size and momentum were present on the cross-section of share returns across 20 emerging markets over the period January 1982 to December 1997. The author found that return factors are quantitatively similar across emerging markets when compared to developed markets. When aggregating the results across the 20 emerging markets analyzed, shares exhibited momentum, small capitalization shares outperformed large capitalization shares and value shares outperformed growth shares. Moreover, in direct contravention of the CAPM, high beta shares did not significantly outperform low beta shares while there seemed to be no apparent liquidity premium present in the emerging markets considered. For the study of momentum in the emerging markets, the author utilized a pre-sort estimation and post formation holding period of 6 months. When implementing the strategy across all of the emerging markets considered, winner shares outperformed their loser counterparts, achieving average excess returns of 0.39% per month and were significant at the 5% level.

Chui, Titman and Wei (2000) examined the profitability of momentum strategies across eight Asian markets over the sample period that began in the latter part of the 1970's and ended in February 2000. The authors found that momentum is present in all Asian markets barring Korea and Indonesia and was generally weak and statistically insignificant post the Asian currency crisis. The authors further found that momentum profits tended to last for approximately ten months post portfolio sort which is less than the 12 month return continuation found in studies conducted in the US. Consistent with US findings, the authors found that momentum in Asian equity markets is relatively stronger for smaller companies, companies with lower book-to-market ratios (growth firms) and higher turnover ratios (more liquid shares). The authors utilized momentum strategies similar to that of Rouwenhorst (1998, 1999) where shares were grouped based on their historical 6 month returns and held for equivalent 6 month portfolio holding periods. A major methodological difference between the study to that of Jegadeesh and Titman (1993) and Rouwenhorst (1998, 1999) was that portfolio returns were calculated on value-weighted and not an equally weighted basis. The authors used two samples, one which included Japanese equities and one which did not (the reason being that the Japanese equity market was far greater in terms of liquidity and market capitalization). When including Japan in the sample, excess average returns of winner over loser shares amounted to 0.376% per month and insignificant. However, when excluding Japan, momentum profits were 1.45% prior to the Asian currency crisis and 0.54% per month post-crisis and were significant at the 1% and 5% level respectively.

Griffin, Ji and Martin (2003) conducted a study on momentum using data from the US and 39 other countries that were covered by the Datastream International database. US data spanned from 1926, however, for 10 of the international markets covered, the data only began in 1975. By 1990, stock return data was available for 23 countries and by 1995 there was data available for all countries considered barring Egypt. The sample period ended in December 2000. The authors used the conventional momentum formation criteria of a 6 month estimation and holding period, consistent with the methodology used by Rouwenhorst (1998, 1999) and Chui, Titman and Wei (2000). The authors found evidence consistent with previous literature as all countries displayed momentum, yet momentum profits in Asia were considerably weaker. The authors found that Africa displayed the highest average momentum profits of 1.63% per month, followed by the Americas who achieved 0.78% per month while European equity markets achieved average momentum returns of 0.77% per month respectively. Consistent with the results of Chui, Titman and Wei (2000), Asian equity markets achieved average momentum profits of 0.32% per month.

Griffin, Ji and Martin (2005) conducted a further study on international momentum profits which differed from their initial study as the authors considered 40 markets when testing for price momentum and 34 markets when testing for earnings momentum. The authors found that the average price momentum profits for all countries considered was 7.98% per year while earnings momentum achieved returns of 5.10% per year. The authors further tested the relationship and

interaction between price momentum and earnings momentum. The authors found that in the America's and Europe, price momentum tends to dominate earnings momentum, yet the inverse was true for Asian markets. Furthermore, it was found that when combining earnings and price momentum in bivariate sorts, the results were noisier yet superior to the average profits achieved in univariate momentum sorts.

The body of South African literature related to the existence of medium term momentum on the cross-section of shares listed on the JSE is considerably sparser than international studies on the subject. Fraser and Page (2000) conducted a study on all industrial shares listed on the JSE over the period January 1973 to October 1997. The authors attempted to identify whether medium term price momentum and value were present on the JSE over the sample period and to further test the interaction between the investment styles. The authors employed a 12 month estimation period and a one month holding period and found that historical winners outperformed historical loser portfolios by 0.76% per month on average, implying that both momentum and value possessed predictive quality when considering the cross-section of industrial shares listed on the JSE ALSI.

Van Rensburg (2001) conducted an in-depth study into the explanatory power of style based risk factors on the cross-section of share listed on the JSE over the period February 1982 to March 1999. Of the numerous style factors considered, medium term momentum featured in the form of momentum portfolios based on 1, 3, 6, 12, and 24 month cumulative historical return windows. Portfolios were formed using each of the estimation periods and were reweighted monthly. The time-series one month excess returns of winners minus loser portfolios were then analysed using a pure CAPM based attribution model as well as an APT style factor model that used the JSE FINDI and RESI as risk factors. For additional robustness two differing sets of momentum portfolios were created, where the first measured momentum against all shares considered (therefore, historical return relative to the entire universe of shares), while the second considered shares that experienced a positive price movement. It was found that momentum profits calculated based on historical 12 month (historical price change included) and 6 month (in relation to the entire sample) estimation periods achieved average monthly returns of 1.52% and 1% respectively. The only momentum portfolio(s) that failed to produce significantly positive excess returns were those that applied a single month estimation period. Furthermore, the raw return results were confirmed by attribution analysis conducted using the CAPM and APT based attribution models. Both the six and 12 month (estimation period) momentum portfolios produced significantly positive alphas under both attribution models.

More recently, Hodnett, Hsieh and van Rensburg (2012) re-examined the payoffs of investment equity styles on the cross-section of shares on the JSE over the period 1 January 1997 to 31 December 2007. The authors considered six variations of price momentum and examined the

significance of the risk premia using Fama-Macbeth style regressions. The authors found that 3, 6, 12 and 24 month momentum provide positive factor payoffs. Hoffman (2012) conducted an in-depth study into the efficiency of the JSE by analysing a number of factor anomalies over the period April 1985 to December 2010. The study found that momentum maintained a positive relationship with future returns and was consistent across size categories, with the winner minus loser excess returns achieving returns between 1.4% and 2.5% per month on average.

Muller and Ward (2013) conducted a graphical time-series approach to testing the success of style based investment strategies on the cross section of the top 160 (by market capitalization) companies listed on the JSE over the period 1985 to 2011. The authors applied a methodology reminiscent of Jegadeesh and Titman (1993) as they attempted to identify the optimality of portfolio estimation and holding periods when applying momentum strategies. The study found that the optimal formation window was the historical 12 months of return while the best performing holding period was 3 months, with the winner minus loser premium being 18.6% per annum on average. Page, Britten and Auret (2013) conducted a study on medium term price momentum on the cross-section of shares listed on the JSE over the period January 1995 to December 2010. The authors found that there was a significant momentum premium over the entire sample period, yet momentum profits seemed to decline in the latter half of the sample (between January 2002 – December 2010). Moreover, the authors found that there seemed to be a significant interaction between momentum profits and liquidity (proxied by turnover), where the highest momentum profits were achieved in the most liquid portfolios.

The current body of South African literature on the presence of momentum on the cross-section of shares listed on the JSE has grown over the past decade yet, pure momentum tests allowing for empirical variations in portfolio construction i.e. variations in both estimation and holding periods, assumptions regarding liquidity and direct transaction costs as well as the interaction between momentum and other investment styles has not been adequately addressed. Furthermore, the interaction between momentum and other noted styles has been limited to single case by case investigations (i.e. momentum and value per Fraser and Page (2000) and momentum and idiosyncratic risk per McLean (2010)). This study intends to utilise both bivariate sorts (dependent and independent) as well as time-series attribution regressions with a combination of internationally and locally considered pricing anomalies in order to decompose momentums independence and covariance with size, value, liquidity, market beta, idiosyncratic risk and currency risk. Of the six pricing anomalies, the latter three differ from the former in that they are by design more computationally intricate and data intensive. For this reason, the former are referred to throughout the study as ‘regressed factors’ and are even tested separately from the former three factors size, value and liquidity in Chapter Four which considered bivariate independent and dependent portfolio sorts.

Lastly (and most importantly), the study intends to extend the current body of knowledge beyond identification and confirmation of independence of momentum by testing momentums' contribution to the cross-sectional variation in share returns on the JSE. The test intends to incorporate the non-momentum pricing anomalies considered in the study, allowing for multivariate tests to determine whether momentum is a principal component or key explanatory variable that drives share returns on the JSE. If momentum is found to be a significant driver of share return variation, then momentum as a priced factor deserves inclusion in factor pricing models that define the risk/expected return relationship for South African equities.

1.2 PROBLEM STATEMENT

In specific reference to the South African literature that considers medium term momentum in share prices, there is a gap in knowledge pertaining to the momentum premium on the JSE. There are a number of studies that prove the existence of momentum, however, there are a series of empirical permutations and further tests that would add significantly to the current body of knowledge. This study intends to test momentum in three effective stages, specifically univariate, bivariate and multivariate. Univariate tests imply solely considering momentum in share prices, allowing for empirical variations in terms of portfolio estimation period, holding period, liquidity and trading cost effects as well as testing for the presence of short and long term reversal. Bivariate tests are to take the form of bivariate independent and dependent sorts conducted simultaneously on momentum and the non-momentum pricing anomalies considered in local and international literature. The basis for applying and analysing both dependent and independent sorts is for the dual purpose of additional robustness and identifying whether empirical variations affect results[2]. The main purpose of the bivariate tests is to identify whether momentum is independent of other noted pricing anomalies and additionally, the level of interaction between momentum and the non-momentum pricing anomalies in order to define both relational qualities and exploitable trading strategies that produce relatively superior investment profits (beneficial covariate structure).

The multivariate tests take two forms, namely the time-series attribution regressions and cross-sectional panel regressions. The attribution regression analysis is an extension of the bivariate sorts, aiming to determine whether other factor premiums present on the JSE explain the variation in momentum portfolio returns. To effectively identify whether momentum is explained by the various factor premiums considered, GRS test statistics are applied in order to determine whether momentum portfolio alphas are jointly equivalent to zero. Time-series attribution regressions are effectively a risk-based test of momentum where the various non-momentum factor premiums are

[2] A number of studies have questioned empirical techniques and their effects on empirical outcomes. Lo and Mackinlay (1990) and more recently Shanken and Weinstein (2006) found that portfolio estimation assumptions affect the determination of factor premiums and betas.

assumed to be risk proxies that contribute to the data generating process governing share returns on the JSE. The purpose of time-series attribution tests in this study is not solely to define whether momentum is driven by non-momentum risk factors. Rather, the central aim of time-series attribution regressions is to determine whether momentum is independent of other priced (and potentially non-priced) non-momentum factors. The cross-sectional panel regressions extend the test from considering the drivers of momentum returns to identifying the contribution of momentum to the cross-sectional variation in share returns on the JSE.

Simply, instead of momentum being the dependent variable, it is now applied in a multivariate setting as an explanatory variable within a share-by-share aggregate framework. The panel qualities of the cross-sectional data allow for the application of a series of econometric models that cater for the potential heterogeneity present in time-series data. The benefit of applying three econometric models as opposed to a single specification is increased robustness as well as defining which of the priced factors are consistently significant irrespective of the econometric model applied. The question of whether momentum is a 'risk factor' is not explicitly considered, rather the goal of the test is to determine whether momentum explains a proportion of the variation in share returns on the JSE and therefore is a 'priced factor'. In summary, this study intends to not only bridge the current gap in knowledge on the subject of momentum on the JSE but to further extend the literature to unexplored empirical areas that are unique and novel in a South African context.

1.3 PURPOSE OF THE STUDY

The purpose of the study is to determine the presence of momentum on the JSE, define whether it is independent and identify the contribution of momentum to the cross-sectional variation in share returns. In order to answer the proposed research questions, a brief discussion surrounding the research design and data is delineated below. The dataset employed throughout the study is the Findata@Wits share database that includes time-series share price data on every instrument listed on the JSE over the time period December 1989 to June 2015. The data base contains monthly return, liquidity and accounting ratio data adjusted for corporate actions. The data set utilised in this study spans over the time period January 1992 to June 2015 and only considers listed companies while excluding investment trusts, cash shells and exchange traded funds (an in-depth discussion regarding the data set is described in section 1.7 that follows). The research design of the study is described in detail in each chapter where the specific empirical variations are applied, however a brief explanation of the various empirical tests is offered in the paragraphs that follow.

In univariate tests, shares are sorted solely on momentum utilising variations in portfolio estimation and holding periods, liquidity and trading cost assumptions as well as allowing for a

single month gap between portfolio estimation and investment in order to determine the presence of microstructure effects or short-term reversal on the JSE. Portfolio returns are then analysed in order to determine whether momentum exists on the JSE (i.e. positive returns across all portfolio variations), the optimal holding and estimation period and whether the application of a single month gap improves returns attained through momentum sorts. Importantly, returns are calculated on a buy-and-hold basis assuming both equal and market capitalization weighting. The benefit of buy-and-hold is described by Lo and Mackinlay (1990) as it allows for a more realistic representation of portfolio returns, where share weightings are only adjusted at portfolio initiation and the allowed to "free float" until the next reweighting or portfolio sort.

Bivariate tests are then conducted by sorting on momentum and a non-momentum pricing anomaly. The non-momentum pricing anomalies considered across this study are the size effect per Banz (1981), the value premium credited to Basu (1977), liquidity proxied by the turnover ratio described by Amihud and Mendelson (1986), market beta and more specifically the low beta effect of Frazzini and Pedersen (2014), idiosyncratic risk described by McLean (2010) and Baker, Bradley and Wurgler (2011) and lastly currency risk as per Barr and Kantor (2005). In bivariate sorts, two methodologies are applied where the first is 'independent' implying sorting simultaneously into one of nine tercile portfolios based on momentum and a non-momentum pricing anomaly. The second methodology applied is a dynamic dependent sort where shares are initially sorted into quintile portfolios based on momentum and then weighted to simulate the non-momentum pricing anomaly. An example of the dynamic dependent weighting strategy would be a test of momentum and value, proxied by the book-to-market ratio.

As described, shares are initially sorted on momentum and are then weighted in order to 'mimic' the effects of the value premium. Shares within the upper quintile momentum portfolios are weighted based on their respective book-to-market ratios while lower quintile constituent shares are weighted based on the inverse of the book-to-market ratio. The obvious result is that winner shares that maintain high value (i.e. high book-to-market ratios) receive higher portfolio weights in the upper quintile portfolios while loser growth shares are assigned the highest weightings in the lower quintiles. The benefit of applying two weighting methodologies is additional empirical robustness as well as the determination of outcome variation due to empirical differences.

Lastly, regression analysis within the study takes two forms, namely; time-series and cross-sectional (panel) regressions. The time-series regressions are intended to test whether the non-momentum pricing factors, i.e. the time-series excess returns earned on size, value, liquidity, low beta and low volatility factor sorts explain the momentum premium on the JSE. The time-series excess returns of momentum portfolios assuming equal, market capitalization and momentum weighting are set as the dependent variable. The momentum returns are then regressed on various factor premiums and both portfolio alphas and factor weightings are analyzed. In order to

determine whether the considered factors successfully explain the momentum premium on the JSE, the GRS test statistic is applied. The benefit of the GRS statistic is that it allows for the joint test of portfolio alphas in determining whether they are 'jointly' significantly from zero. Hypothetically, if portfolio alphas are jointly equal to zero, the implication is that the factor premiums applied lie on the efficient frontier and therefore completely explain the overall variation in dependent portfolio returns.

Finally, cross-sectional or panel regressions are conducted on a share-by-share basis where single share average returns replace momentum portfolios as the dependent variable. Once again, the non-momentum factors are applied as explanatory variables, yet momentum is now included as an independent explanatory variable. The nature of the data, where both time-series and cross-sectional properties are present, allows for the application of panel data models as opposed to running Fama and Macbeth (1973) two pass regressions which are common in practice but methodologically and econometrically inferior to panel specific econometric models. The models applied within the cross-sectional analysis are the pooled OLS, fixed effects and random effects models. The benefit of both the fixed and random effects models is that both allow for the modeling of cross-sectional and period specific heterogeneity, both of which can affect the consistency and efficiency of estimated regression coefficients. A further benefit is the additional robustness achieved through the application of three as opposed to a single model specification, allowing for the assessment of consistency of factor signs and coefficients across the various econometric models applied.

1.4 SIGNIFICANCE OF THE STUDY

As described in the Section 1.1 *supra*, the significance of the study is directly linked to the current gap in knowledge specific to South African literature regarding the momentum premium on the JSE, what drives momentum and whether momentum in share prices contributes to the cross-sectional variation in share returns. The implications of answering the research questions posed in this study are far reaching and pertinent to academics and practitioners in the fields of corporate finance and investment. Firstly, the identification and independence of momentum on the JSE would be a further significant drawback for the CAPM and market efficiency on the JSE. Furthermore, it would augment the international, and specifically emerging market literature on the momentum effect as South Africa is considered to be at the forefront of emerging equity markets, ranking fifth in the Morgan Stanley Composite Index emerging markets and is a member of the BRICS countries.

The identification of a consistent momentum premium as well as the optimal combination strategies is key to investment and money managers, both for the purpose of risk attribution analysis and optimal active and passive investment strategy development. Practitioners are

driven to attain excess returns in the form of alpha and further decompose their holdings on a risk basis, implying identifying the drivers of alpha as well as factor exposures. If momentum is found to be both significant and independent, fund attribution and performance analysis metrics would require a proxy factor for momentum or risk possible misspecification thereby depicting incorrect levels of alpha. Additionally, the determination of an unbiased independent momentum factor that contributes to the variation in share returns on the cross-section of equities listed on the JSE would lay the foundation for new streams of literature on appropriate pricing models that can be applied in equity analysis, valuations and corporate finance.

The majority of South African asset pricing literature has centred on the Fama and French (1992, 1993 and 1996) size and value factors or the Chen, Roll and Ross (1986) APT style macro-economic factors. Logically, the discovery and incorporation of 'new' factors within an asset pricing model are required if found that the said factors drive share returns. For this purpose, the final chapter of this study conducts a share-by-share panel based aggregation of factor premiums on the JSE and incorporates previously considered factors such as size and value but further considers largely unexplored pricing anomalies such as liquidity, low volatility, low market beta, currency risk and most importantly, momentum. By defining a more efficient factor pricing model, company valuations, risk attribution studies and asset manager performance attribution would benefit with a higher degree of certainty pertaining to estimates of the cost of equity, weighted average cost of capital, risk or factor exposures and risk-adjusted returns or alpha.

1.5 PRIMARY RESEARCH QUESTIONS

The primary research questions posed in this study are directly related to the purpose of the study, specifically a detailed examination of momentum on the JSE. As described, the analysis can be divided into four sub-areas where each can be described as a specific research question related to the study of momentum on the cross-section of shares listed on the JSE. The first research question is "Is momentum present on the cross-section of shares listed on the JSE?" which then extends to studies of momentum on a univariate basis as per Jegadeesh and Titman (1993, 2001). Empirical permutations are explored related to variations in portfolio estimation and holding periods, liquidity and trading cost effects as well as whether short and long-term reversal affects momentum returns. The research question is then extended to consider whether momentum is explained by the non-momentum factors employed throughout the study. Importantly, the extension is a bivariate test where momentum and the non-momentum pricing factors are applied in bivariate sorts to determine independence as well as interaction. A natural extension of the test is the testing of momentum in a multivariate setting where momentum returns are regressed on the non-momentum factors using time-series attribution regressions. Therefore, the research question evolves to "Do non-momentum pricing anomalies explain momentum on the JSE?" The final component of the research question is considered in cross-sectional regression tests. At this

juncture in the study, if momentum is both present and independent on the JSE and therefore not driven by other pricing anomalies, the penultimate research question is “To what extent does momentum contribute to the cross-sectional variation in share returns?” or more succinctly “Is momentum an independently priced factor on the JSE?"

1.6 HYPOTHESES

The hypotheses of the study follow from the primary research questions expressed in Section 1.5 above. The hypotheses are delineated in point form below with each hypothesis being labelled with Roman numerals to represent the specific research question, *S* indicates a sub-hypothesis and conventional numerals refer to the null (0) and alternative (1).

1.6.1 Univariate tests of momentum (Hypothesis I)

$H_{I,0}$: The momentum premium does not exist on the JSE, irrespective of estimation and holding period and liquidity or trading costs.

$H_{I,1}$: The momentum premium does exist on the JSE and is sensitive to empirical assumptions related to estimation and holding period and liquidity or trading costs.

- Hypothesis I contains a number of sub hypotheses:

$H_{IS1,0}$: There is no effect on momentum profits given empirical variations related to portfolio estimation and holding periods.

$H_{IS2,0}$: There is no effect on momentum profits given empirical variations related to liquidity and price impact.

$H_{IS3,0}$: There is no effect on momentum profits given empirical variations related to equal and market capitalization weighted returns

$H_{IS4,0}$: Micro-structure effects and short-term reversal are not present on the JSE and therefore have no effect on momentum profits.

$H_{IS5,0}$: Momentum returns do not reverse given portfolio holding periods in excess of 12 months.

1.6.2 Bivariate tests of momentum (Hypothesis II)

$H_{II,0}$: The momentum premium is explained by one of the non-momentum factors in bivariate sorts i.e. variations in momentum portfolio assumptions (winner, medium and loser) do not result in variations in portfolio returns.

$H_{II,1}$: The momentum premium is not explained by one of the non-momentum factors in bivariate sorts i.e. variations in momentum portfolio assumptions (winner, medium and loser) results in variations in portfolio returns.

- Hypothesis II contains a two sub-hypothesis

$H_{IIS1,0}$: Momentum returns display no variation across bivariate sorts implying limited interaction between momentum and the non-momentum factor anomalies considered.

$H_{IIS2,0}$: There is no effect of applying empirical variations related to independent and dependent bivariate sorts.

1.6.3 Time-series multivariate tests of momentum (Hypothesis III)

$H_{III,0}$: The risk-adjusted return (alpha) achieved by portfolios sorted on momentum is wholly or largely explained by the risk premiums of the non-momentum factors considered.

$H_{III,1}$: The risk-adjusted return (alpha) achieved by portfolios sorted on momentum is not explained by the risk premiums of the non-momentum factors considered.

- Hypothesis III contains a single sub-hypothesis

$H_{IIIS1,0}$: Momentum risk-adjusted returns are insensitive to portfolio weighting methodologies (equal, market capitalization and momentum weightings)

1.6.4 Cross-sectional multivariate tests of momentum (Hypothesis IV)

$H_{IV,0}$: Momentum fails to explain the cross-sectional variation in share returns on the JSE and is therefore not a priced factor.

$H_{IV,1}$: Momentum is a priced factor and therefore explains a signifncat portion of the cross-sectional variation in share returns on the JSE.

- Hypothesis IV contains two sub-hypotheses

$H_{IVS1,0}$: Momentum is inconsistent across econometric specifications.

$H_{IVS2,0}$: None of the factors (momentum, size, value, liquidity, volatility, liquidity adjusted beta and currency risk) describe the cross-sectional variation in share returns on the JSE.

1.7 DATA DESCRIPTION

The School of Economic and Business Sciences (SEBS) financial database ("Findata@Wits" hereafter) will be utilised to define the sample and time frame used in the study. The database spans over the period January 1989 to June 2015 and contains financial information on every share listed on the Johannesburg Stock Exchange over the sample period. The database is holistic as no share is excluded based on market capitalization or liquidity. In order to deal with survivorship bias, a share is immediately included in the database from the first month of listing while shares that delist are assigned a "not listed" code and are retained in the database. As a share comes into the database, it is assigned a first true code which precludes the possibility of structural breaks due to name changes, share splits and unbundling's.

Monthly 'raw' price returns are calculated for each share within the database, where share prices are adjusted for all corporate actions barring dividends. Total returns are also calculated on a monthly basis where dividends and other corporate actions that result in dividend like payments to shareholders are reflected. The significant corporate actions that generally have a major effect on a shares return and therefore negate the usage of 'raw' returns are unbundling's (share lists a subsidiary and distributes a portion of shares to current shareholders), consolidations (number of shares are consolidated by a factor e.g. ten to one), share splits (subsidiary lists or inverted merger), delisting due to suspension or scheme of arrangement (suspension results in a 100% negative return while delisting due to a scheme of arrangements such as a management buy-out results in a positive return) and lastly, dividends inclusive of special dividends. Each corporate action is recorded and applied to return calculations as well as the calculation of number of shares in issue. The database also contains monthly accounting ratios in the form of earnings yield, book-to-market ratios, dividend yield and cash flow to price. Importantly, all accounting ratios are calculated in a consistent manner that excludes the possibility of look-ahead bias as accounting information is assumed to reach the market six months post the company's financial year end. Liquidity and size data takes the form of monthly volumes, zero daily trades, market capitalization and number of shares in circulation.

The length and breadth of the database lends credence to the study as the database is consistent in its treatment of shares, calculation of returns and ratios, treatment of corporate actions and their effects on share prices and returns and no application of initial exclusion criteria. Therefore, data collection, survivorship bias and look-ahead bias, which are all significant issues when dealing with studies of this nature, are controlled for. The initial time-period is set to January 1992 as both dividend and liquidity data are inconsistent over the period December 1989 to December 1991. Over the sample period January 1992 to June 2015, there are 1402 shares (unique first true codes) in the database.

The data specifically excludes investment trusts, cash shells and exchange traded funds as such entities are considered non-trading entities and do not represent operating companies. A further filter is applied where each share requires at least 12 months of consistent returns. The application of the filter results in the culling of 189 shares leaving a cross-section of 1213 shares (unique first true codes) over the sample period. Across the sample period considered in this study, the average number of unique first true codes or investable shares per month is 493.21. Notably, the average number of listed shares varies significantly across the time-period considered, with the average number of investable shares reaching a maximum of 679 in January and February 2000 and a minimum of 376 in October 2014. Despite the decreasing number of shares, the JSE has experienced a significant increase in overall liquidity when proxied by average volume. The figure that follows describes the average number of shares and average volume per annum.

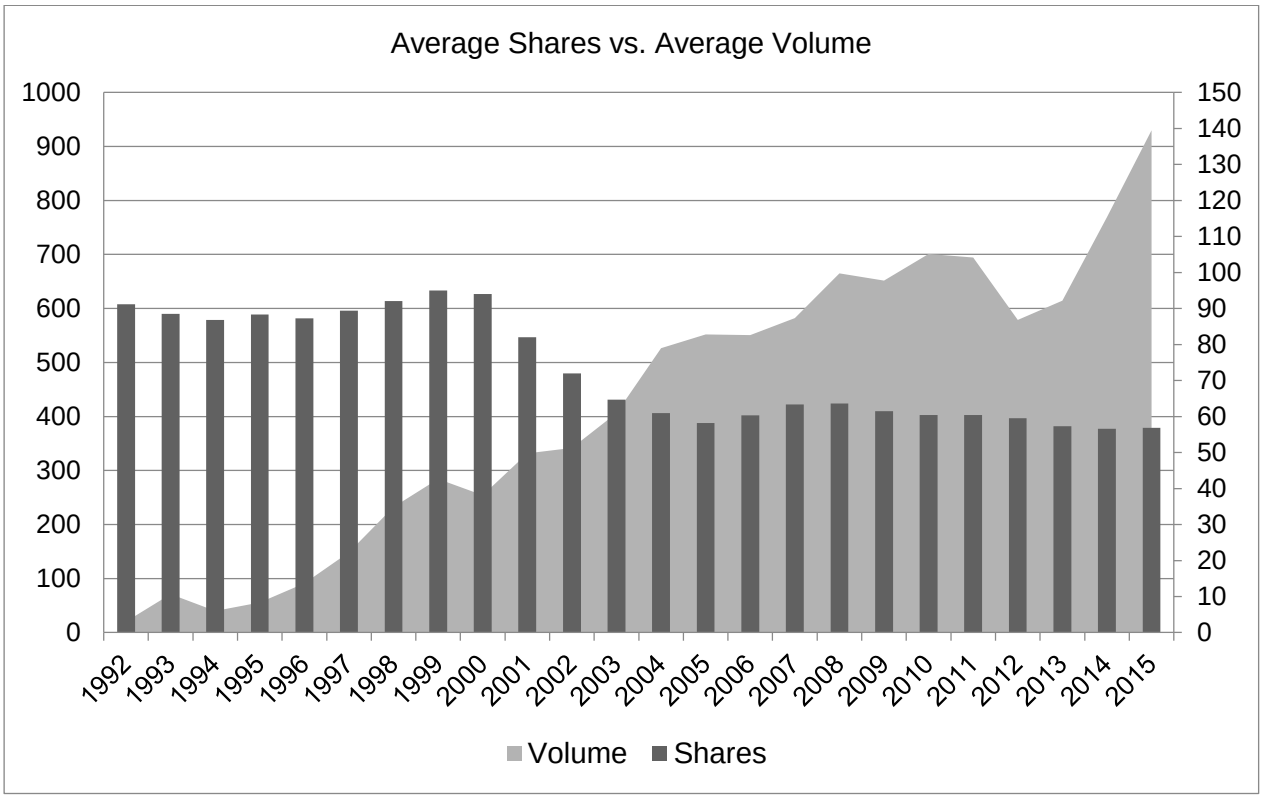


Figure 1.1: Average number of listed shares versus scaled average monthly volume

Figure 1.1 above depicts the average number of shares versus the average monthly volume per annum scaled by 100 000 where volume represents the total average number of shares traded over a calendar year. As described above, the figure clearly indicates that the number of shares on the JSE has decreased significantly, indicating a 40% decrease when comparing the maximum and minimum number of shares across the time-period. Conversely, the average volume has increased dramatically, indicating a 4 462% increase in average monthly volume from 1992 to 2015. Across the various empirical tests conducted throughout the study, various filters are applied that constrain the universe of shares. The specific filters applied relate to price as a proxy

for trading costs, liquidity based on turnover (volume scaled by number of shares in issue), cumulative zero daily trades over the previous annum and the natural log of market capitalization. The result is that within each test, the universe of considered shares varies in accordance with the empirical methodology applied and the specific requirements in terms of liquidity, price impact and trading costs. Importantly, the empirical description within each chapter defines both the data and the specific filters applied resulting in the final universe of shares on which the various tests and tests are to be conducted.

1.8 THEORETICAL FRAMEWORK

The theoretical framework of this study is asset pricing, the relationship between risk and return as well as the efficient market hypothesis. Markowitz (1952) stated that the risk of an asset should be the sole determinant of expected return. The theory was further extended by Sharpe (1964), Lintner (1965) and Black (1972) to consider the effects of diversification and the result was a two-parameter model that consisted of a risk-free or zero beta asset and an ex-ante efficient market portfolio, otherwise known as the CAPM. Fama (1970) is formally credited with the theory of efficient markets which is directly linked to the development of the CAPM and the relationship between risk and expected returns.

The weak form efficient market hypothesis (“EMH” hereafter) dictates that historical information is incorporated in share prices implying that trading strategies that rely on the historical information should not result in excess continued returns. Linking the EMH to the risk-return relationship of Markowitz (1959) and the CAPM; as information is incorporated in share prices, investors are not compensated for trading on the said information and therefore, the only driver of returns should be the underlying risk of the asset borne by an investor. The EMH and CAPM have been the subject of extreme scrutiny and academic challenges resulting in two avenues of rebuttal, the first being that risk is multi-dimensional while the other disputes risk as the driver of returns in favour of behavioural biases. The study to be conducted is empirical and focuses on the momentum pricing anomaly. The presence of momentum (or rather a positive momentum premium) contravenes the conventions espoused by the EMH and the CAPM. If momentum produces significantly positive returns, such would imply that information in share prices is exploitable and similarly not related to identifiable risks.

The research to be conducted forms part of the stream of literature related to pricing anomalies that refute the CAPM and EMH. Furthermore, evidence of momentum (and long-term reversal) has resulted in a divergent theory related to behavioural biases governing share prices. Chen, Roll and Ross (1986) and Fama and French (1992) considered both pricing anomalies and the inability of the CAPM to describe the risk-expected return relationship and created a further stream of research related to determining factors that drive share returns. Chen, Roll and Ross

(1986) considered the work of Roll (1977) where the author hypothesized that the CAPM is untestable due to the impossibility of determining the market portfolio. Chen, Roll and Ross (1986) developed the APT model that considers macro-economic state factors that explain share returns. Fama and French (1992) consolidated all pricing anomalies into single study and found that size and value, when incorporated within a pricing model, explain a majority of the variation in share returns in US equities. This study is conducted in the same vain in that it intends to define whether momentum is present, independent and describes a proportion of the cross-sectional variation in share returns listed on the JSE. Therefore, the results of the research to be conducted have material implications for the EMH and the application of the CAPM on the JSE, as well as an appropriate asset pricing specification for the South African market. Importantly, the notion of whether momentum is indeed a risk-factor is not directly considered. Importantly, and key to the research question posed in this study, the presence of an independent anomaly that drives share returns without an *a priori* risk description cannot preclude such a factor being a priced. Therefore, the study will empirically evaluate the presence of momentum and whether it explains the variation in expected share returns on the JSE without attempting to define a risk or behaviourally based explanation of momentum.

1.9 ASSUMPTIONS, LIMITATIONS AND DELIMITATIONS OF THE STUDY

The base approach of the study is empirical as opposed to theoretical and therefore is highly dependent on both the data and research methodologies applied. Unfortunately, there is no South African or African version of the Centre of Research in Share Prices ("CRSP" hereafter) database and hence, data is a natural limitation. The Findata@Wits database is unique in the South African context as it contains the entire cross-section of listed shares on the JSE over the period December 1989 to date. The data pre-1992 is limited in terms of liquidity and dividend data accuracy, hence this study only considers the period January 1992 to June 2015. The usage of the Findata@Wits database entails that a number of the core assumptions related to the data are applied in this study (refer to section 1.7 for a description of the data). A number of other core assumptions are made related to the theoretical framework applied to the research methodology employed within the study.

Firstly, no pre-emptive assumption is made that the CAPM is true. Secondly, and more importantly, since the final chapter intends to define whether momentum contributes to the cross-sectional variation in share returns, to some extent, this study does hold by the weak form of the EMH and APT model of Chen, Roll and Ross (1986). The weak form of the EMH implies that historical information is contained in share price data and therefore, only additional risk borne should result in increased expected return. The APT framework of asset pricing precludes the requirement of defining an *a priori* theory, but rather relies on empirically defining the principal components that govern the data generating process of share returns assuming that factor premia

(or risks) describe expected returns. Therefore, the methodology applied within this study is typically empirical as it intends to determine the presence and consistency of momentum and then conclude whether momentum explains the cross-sectional variation in share returns on the JSE.

An obvious limitation is the small universe of shares on the JSE as well as the relatively limited time-series, especially when compared to international databases. A further limitation relates to the study of emerging market momentum. The JSE is considered a prominent force amongst the emerging markets, however, it would be ideal to expand the study to other African markets in order to develop a complete study related to momentum on a continental level. Specific delimitations of the study relate to the time period considered where the first four years of the Findata database are excluded, the enforced limitation related to the investability of the universe of shares considered within the study and lastly, the specific avoidance of defining whether momentum is a risk or behavioural bias.

The latter two points require further discussion. As mentioned, the power of the Findata@Wits database is that it is unbiased as it includes every share ever listed on the JSE. Unfortunately, not every share can be included within an empirical study of this nature as illiquidity and price impact can cause significant outliers that skew results. Most empirical studies and literature that contemplate asset pricing and factor anomalies describe the enforced limitation on the data in order to ensure that the results are both realistic and not affected by significant outliers. Therefore, across this study, the data are subjected to significant purging in order to limit the effects of outliers and to ensure the highest level of realism in terms of outcomes and evidence (a description of the data assumptions are given in each chapter that deals with an empirical question). The purpose of the study and core research questions relates to the identification of momentum (univariate), the independence of momentum (bivariate sorts and multivariate time-series) and whether momentum drives share returns (multivariate cross-sectional). In univariate sorts, evidence in favour of momentum and long-term reversal is consistent with the behavioural biases such as self-attribution and under/overreaction.

However, the sole purpose of the test is empirical in that it only intends to define whether momentum is present and whether momentum profits are reversed in the long-term. The multivariate tests, specifically time-series attribution regressions, are typically applied in literature in attempting to determine whether noted “risk” factors explain the momentum premium. The risk-based approach is discussed, but there is no *a priori* assumption made about the explanatory variables applied being “risk” factors and are generally referred to as ‘factor premiums’ to avoid confusion. The core purpose of the time-series attribution regressions is to determine whether momentum produces significant excess returns (“risk-adjusted returns”) in a multivariate setting, hence once again attempting to determine whether momentum is independent when considered

in conjunction with other pricing anomalies. The cross-sectional analysis can also be viewed from a risk-based pricing framework, similar to that of Fama and French (1992), in that the study will attempt to define the pricing anomalies that maintain descriptive power and explain the variation in share returns on the JSE. The study however does not explicitly consider the nature of the risks or whether the factors themselves are risks but rather focuses on the empirical evidence related to the said factors and their ability to describe the cross-sectional variation in share returns on the JSE. The premise of the study can therefore be summarised as identification of the factor, scrutiny of the factor in a multivariate setting and finally, defining whether the factor explains the cross-sectional variation in share returns. If the criteria of the above paradigm are met by the momentum anomaly on the JSE, one can conclude that momentum is a state priced variable that describes share returns on the JSE and therefore deserves inclusion in any asset pricing framework defined for equities on the JSE.

1.10 CHAPTER SUMMARY

The study to be conducted intends to prove the presence, significance and independence of momentum in short to medium term share prices on the JSE. The envisioned study aims to extend the current body of evidence related to momentum on the JSE by first applying univariate tests of momentum using the methodology of Jegadeesh and Titman (1993), allowing for optimization based on estimation period, holding period, liquidity and price impact filters as well as the effect of equal and market capitalization weighting returns.

The study further intends to fill the current gap in the body of literature by attempting to answer whether momentum is independent of other non-momentum pricing anomalies considered. The independence of momentum is tested by first conducting independent and dependent bivariate sorts using momentum and the other non-momentum pricing anomalies. The study further considers the independence of momentum in a multivariate setting by regressing momentum portfolio returns on non-momentum factor premiums. Time-series attribution regressions allow for testing whether risk-adjusted (factor adjusted) momentum profits or alphas are significantly positive. The final test is also multivariate in nature but differs to the time-series attribution regressions in that it attempts to determine whether momentum describes the cross-sectional variation in share returns on the JSE.

The obvious intention of this study is an exhaustive exploration into the momentum premium on the JSE, ranging from the identification of momentum, the potential profits attributable to momentum sorts, the independence of momentum and its interaction with other pricing anomalies, whether momentum is explained by other pricing anomaly premiums on a risk-adjusted basis and lastly, the contribution of momentum to the cross-sectional variation in share returns listed on the JSE. Chapter Two that follows provides a comprehensive review of

momentum literature relating to the momentum anomaly, US, international (Non-US) and South African literature on momentum as well as literature related to risk and behavioural based explanations of the momentum premium. Chapter Three considers univariate tests of momentum applying the methodology of Jegadeesh and Titman (1993); Chapter Four bivariate tests of momentum; Chapter Five examines the momentum premium using time-series attribution regressions; Chapter Six attempts to prove whether momentum explains a proportion of the cross-sectional variation in share returns on the JSE via panel data cross-sectional regressions, Chapter Seven summarizes the main results of the study and concludes.

CHAPTER TWO LITERATURE REVIEW

2.1 INTRODUCTION TO MOMENTUM AS AN INVESTMENT STYLE

Prior to the seminal paper by Jegadeesh and Titman (1993), momentum as an investment style was largely unexplored while reversal in share prices or overreaction, attributed to De Bondt and Thaler (1985), was highly topical over the latter half of the 1980's. The concept of momentum in share prices over the medium or short term was previously considered in literature under the guise of "relative strength strategies". Levy (1967) considered a trading strategy that invested in shares that traded at a significantly higher price level in excess of their 27-week average. The author found that such a strategy resulted in significant excess returns. Copeland and Mayers (1982), Stickel (1985) and Grinblatt and Titman (1989,1992) all found that relative strength strategies (the purchasing of shares trading at a premium to their historical values) was prevalent amongst top performing mutual fund managers, where a possible source of the abnormal performance was attributable to the purchase of winning shares. Literature on long-term reversal considered two extreme horizons, where Jegadeesh (1990) and Lehmann (1990) found evidence of price reversals over extremely short time horizons (between one day, one week and one month) while De Bondt and Thaler (1985) found evidence of reversal or overreaction in share prices over extremely long time horizons (36 to 60 months).

Reversal in share prices has been dubbed "overreaction" due to the psychological explanation behind its occurrence. Market participants tend to not follow the envisaged path of processing information based on Bayes' rule (the implication of *appropriately* re-weighting probability distributions based on new information), rather they overweight more recent information and thereby neglect important historical information. A plethora of studies followed the seminal paper of De Bondt and Thaler (1985, 1987), some in favour of overreaction and a number that question the validity of long-term reversal from both an existential and empirical perspective. Jegadeesh and Titman (1993) focused their study on an investment horizon that was largely unexplored in the popular investment anomaly literature. The authors considered the profits attributable an investment strategy that fictitiously bought historical "winning" shares and simultaneously sold historical "losers" over a medium-term investment horizon, where the 'medium-term' was classified as being between 3 and 12 months post portfolio formation. The authors applied the strategy to all shares considered by the center of research in share prices ("CRSP" hereafter) over the period 1965 to 1989. The methodology applied varying portfolio holding periods (*K*) and portfolio formation periods (*J*) where both J and K took on the values of 3, 6, 9 and 12 months, resulting in 16 test portfolios. Shares were cross-sectionally sorted based on their time-series cumulative returns and divided into one of ten decile portfolio where the extreme portfolio were classified as "winners" (shares with the largest cumulative return values over *J* formation months) and "losers" (shares with the lowest cumulative returns over the *J* formation months). In order to

improve the efficiency of the tests, overlapping portfolio sorting periods was applied where shares were sorted monthly and returns were calculated on an equally weighted buy-and-hold basis. Importantly, the authors used two sorting procedures, the first assuming no time gap between sorting and investing while the second allowed for a one week gap in order to account for bid-ask bounce and short-term reversal found in the prior literature (generally referred to as microstructure effects). The result was the simulation of 32 test portfolios, formed on varying portfolio and estimation periods and differing assumptions related to the allowance of a time-period 'gap' between portfolio estimation and formation.

The authors found that all of the zero-cost strategies (i.e. excess returns) that fictitiously bought historical winners and simultaneously sold historical loser shares produced positive returns to the extent that 31 of 32 portfolio simulations realized average excess returns that were statistically significant. The authors found that the allowance one week gap between portfolio formation and holding (investing) resulted in increased profit, indicating that short-term reversal and micro-structure effects were present on the cross-section of shares considered. In order to qualify their results, the authors attempted to decompose the profits attributable to medium-term momentum by analyzing cross-sectional variation due to state factors and to autocorrelation within the error structure of momentum profits. In the first instance, two return generating models were considered where the first was dependent on market risk and the second firm specific risk, proxied by market capitalization (size).

Post-ranking betas were estimated for each of the momentum portfolios by regressing portfolio returns on a value-weighted index of all shares within the CRSP database. The findings showed that the post-ranking market beta produced a U shape, where the extreme portfolios (historical winners and losers) both produced economically high betas, while the intermediate portfolios produced betas that were significantly low. More importantly, the post-ranking beta of the extreme loser portfolio was higher than that of the extreme winner, implying that market risk failed to explain the momentum phenomenon. The authors then analyzed the average market capitalization of the momentum portfolios and found that both the winner and loser portfolios contained smaller shares on average, with the loser portfolio constituents being smaller in terms of average market capitalization when compared to that of the winner portfolio. The analysis therefore proved that momentum profits achieved over the period analyzed were not driven by market risk or size.

When considering the correlation within the momentum portfolios error structure, the authors found that the positive serial covariance identified within the market model residuals suggested that a source of momentum profits might be due to market participants underreacting to firm specific information. In order to further test the potential time-series aspect of momentum profits, the authors employed the methodology of Lo and MacKinlay (1990) by regressing momentum

profit returns on the squared lagged demeaned value weighted market index. The purpose of the test was to identify whether momentum profits conformed to the lead-lag effect, which in essence implies that returns conform to an error correction model that corrects contemporaneously under the assumption that stock prices maintain a delayed reaction to common factors. The authors found that the coefficient on the squared lagged market variable was significantly negative; implying that momentum profits could not be explained by the lead-lag effect implying that the source of momentum profits was probably being driven by market participants underreacting to firm specific information, subsequently referred to as “underreaction”.

Jegadeesh and Titman (1993) concluded that their results required a more sophisticated model for investor behavior as neither market risk, firm specific risk (proxied by size) nor the lead-lag effect could successfully explain profits attributable to momentum strategies. Consistent with the findings of De Bondt and Thaler (1985, 1987), the authors produced evidence that favoured a behavioral model that explains the momentum phenomenon, paving the way for multitudes of literature attempting to define the consistency and source of momentum profits. The literature review to follow attempts to consider and consolidate the global evidence of momentum, the divergent views regarding the sources of momentum profits exploring both risk and behaviorally based explanations, evidence of momentum internationally and locally and the interaction between momentum and other factors that have been used to explain the cross-sectional variation in share returns.

2.2 INTERNATIONAL EVIDENCE OF PRICE MOMENTUM

2.2.1 Evidence of price momentum in the United States

Currently, there is a surplus of international evidence documenting the returns achieved from buying historical winning shares and simultaneously shorting historical losers. Due to the simplistic application of momentum as an investment strategy, requiring only price level data of the asset in question, studies of momentum have transcended the universe of equities and have been applied to fixed income instruments, derivatives and commodities, where evidence consistently depicts that the momentum is present in all assets that have publicly available market prices. Importantly, the nature of this study is solely based on momentum in share prices, hence the literature to be reviewed will focus mainly on equity based evidence of momentum (the vast majority of momentum literature is premised on share prices, hence such a limitation should not hinder the breadth and depth of the literature review to be presented). The following section will endeavor to summarize the international evidence of momentum in share prices. In attempt to develop a logical flow of evidence of momentum in asset prices, the review will attempt to chronologically document the progression of the study of momentum geographically and then to further consider explanations of momentum and adjacent themes of investment and asset pricing.

As mentioned, Jegadeesh and Titman (1993) are credited with the seminal study of short to medium term momentum on the cross-section of US shares (NYSE and AMEX) over the sample period 1965 to 1989. The study found that of the 32 zero cost momentum strategies applied to the data, all achieved positive excess returns with 31 being statistically significant. The best performing strategy utilized a formation period of 12 months (J=12) and a portfolio-holding period of 3 months (K=3) and achieved a significant excess return of 1.31% per month, equating to an annual return of 15.72%. The authors also noted that the six-month formation period (J=6) portfolios, irrespective of holding period achieved excess monthly returns of 1%. Lastly, the authors found that an allowance for a week between sorting and investing periods resulted in increased returns to each of the momentum sorts.

Fama and French (1996) considered a number of trading anomalies, where 'anomalous' implies the failure of CAPM explaining excess performance. The authors intended to prove that the Fama-French three factor model (defined in Fama and French (1993)) was capable of explaining all noted pricing anomalies explored over the past two decades, including medium-term price momentum described by Jegadeesh and Titman (1993) and long-term reversal documented by Debondt and Thaler (1985). The authors considered a sample period from January 1931 to December 1993 using the cross-section of NYSE shares on the CRSP files over the sample period. Using overlapping monthly portfolio formations and allowing for a one month gap between portfolio formation and investment, the authors found that previous medium term loser shares did not achieve excess returns above the risk free proxy, however previous winners achieved excess returns of 1.31% per month. Similarly, the authors also found evidence of long-term reversal in share prices, where historical losers (measured over the previous 60 months) achieved excess returns' over previous winners by 1.35% per month. Most importantly, the authors found that that the Fama-French three factor model successfully explained long-term reversal in share prices however failed to explain medium term momentum returns and stated that the momentum anomaly is the biggest stumbling block to the efficient market hypothesis describe by Fama (1970) and the CAPM.

Chan, Jegadeesh and Lakonishok (1996) considered momentum in share prices and attempted to link price momentum to earnings momentum. The authors considered all US shares listed on the NYSE, AMEX and NASDAQ over the sample period January 1977 to December 1993. Using the methodology applied by Jegadeesh and Titman (1993), the authors considered price momentum using six month portfolio formation periods, sorting shares into one of ten deciles and calculating the overlapping equally weighted average returns, allowing for 6, 12, 24 and 36 month holding periods. The authors found that historical winner portfolios outperform historical losers by 1.3% per month on average. The test extended the analysis to consider the additional characteristics of the momentum portfolios, specifically considering the book-to-market ("BM" hereafter) and cash flow-to-price ratios ("CP" hereafter) of the constituent shares. Both the "in

portfolio" BM and CP characteristics of the tests portfolios showed that loser portfolios were generally made up of shares with relatively higher BM and CP shares (typically value shares) while winner portfolios were made up of glamour or growth shares. The authors then evaluated the past earning performance of the momentum portfolios. Three differing measures of earnings performance were used, namely standardized unexpected earnings (SUE), abnormal returns around earnings announcements and lastly, revision in analysts' forecasts. The findings showed that there was significant in-portfolio variations between the winner and loser portfolios when considering the innovation in their past quarterly earnings (SUE). Similarly, past abnormal announcement returns tended to increase monotonically as portfolios varied from historical losers to winner shares and lastly; winner shares tended to experience greater upward revisions in analysts' forecasts when compared to previous losers. When conducting combined sorts on earnings and price momentum, the authors found that both momentum drivers were present, and although positively correlated, were actually independent. The authors found that each variable considered (prior six month return and the three measures of earnings surprises) adds additional return when holding one of the variables constant. Interestingly, the authors further found that earnings based momentum tends to reverse at a faster rate post sort, entailing that price momentum is relatively more persistent. The findings were further confirmed with Fama-Macbeth cross-sectional regressions where regressions were run assuming that a shares previous six month return and the three variables used as proxies for unexpected earnings shocks were used as regressors. The regression results indicated that each variable maintained statistical significance, and more importantly, that price momentum was not subsumed by any of the earnings momentum proxies considered.

Asness (1997) considered the interaction between momentum and value over the sample period July 1963 to December 1994 and considered all shares listed over the time period on the NYSA, Amex and NASDAQ firms covered by CRSP and the Compustat database. In order to proxy momentum, the study considered the previous 12 month cumulative share return, excluding the most recent month in order to mitigate the effects of bid-ask bounce and used dividend yield ("DY" hereafter) and book-value per share as proxies for value. In univariate tests of momentum, assuming value-weighted portfolio returns, winner portfolios achieved significant excess returns over previous losers of approximately 0.87% per month. Interestingly, the author found that value strategies (when sorting shares based on DY and BM as a value proxy) produces significantly positive excess returns over growth or glamour stocks. The findings presented an interesting dynamic as momentum portfolios tended to overweight growth or glamour shares while value portfolios generally tended to overweight historical losers. The quintessential finding of the study was that momentum and value maintain a consistently negative covariance structure, implying that momentum and value are not only independent but possible state factors that explain the cross-sectional variation in shares returns.

Moskowitz and Grinblatt (1999) considered industry momentum and the effects on individual share momentum. The sample assumed all shares on CRSP files and datastream database over the period July 1963 to July 1995. Using a method reminiscent of that applied by Jegadeesh and Titman (1993), portfolios were sorted monthly using six-month portfolio estimation and holding periods. Contrary to the methodology of Jegadeesh and Titman (1993), portfolio returns were calculated on a value-weighted basis and excess return were calculated assuming winner and loser portfolios were defined by the 30th and 60th percentiles. The methodological variation resulted in the winner minus loser portfolio achieving excess average returns of 5.16% per annum (0.43% per month), drastically economically lower than momentum profits described in prior literature but statistically significant at the 1% level. Using the entire universe of shares over the sample period, the authors sorted shares into one of 20 value-weighted industry portfolios based on the generalized SIC codes. The authors then used an identical method to the single share momentum portfolio sorts by sorting the industry indices based on their six-month historical return. Industry momentum returns were then defined by fictitiously buying and simultaneously shorting the top and bottom three industry portfolios. The industry momentum strategy achieved excess returns of 5.17% per annum on average, virtually identical to the returns achieved by the momentum strategy applied to individual shares. In order to identify whether industry momentum was a driver of individual share momentum, the authors calculated industry adjusted profits by reducing each individual share by its contemporaneous industry return. After adjusting single shares by their industry momentum, individual momentum profits were reduced to 0.13% per month (1.56% per year), yet were still significant at the 5% level. However, when also adjusting for size and value, the adjusted momentum profits become negative on average and insignificant. The findings indicated that a major portion of individual momentum return was explained by industry momentum over the same time period.

Lee and Swaminathan (2000) considered the effects of trading volume, generally used as a proxy of liquidity, on momentum profits. The sample consisted of all firms listed on the NYSE and AMEX over the period January 1965 to December 1995. The study explicitly excluded NASDAQ shares due to their notorious illiquidity and possible double counting of volume estimates discovered by Gould and Keidon (1994). In order to account for differences in cross-sectional trading volume, shares were independently sorted into one of ten portfolios based on historical cumulative return and one of three portfolios based on historical trading volume. The authors found that when conducting a dual sort on momentum and turnover, a significant liquidity premium emerges, yet does not apply to momentum. For example, using a portfolio formation and holding period of six and nine months, low volume loser shares outperformed high volume losers by 1.02% per month on average while low volume winners outperformed high volume winners by 0.26% per month on average. The findings are consistent with the illiquidity premium hypothesis, yet when considering the excess returns of winners over losers, the high volume momentum excess returns were

superior to that of the low volume sorts. Considering the six month estimation and holding period momentum strategy, high volume excess momentum returns were 1.46% per month while the low volume excess returns were 0.54% per month and the 0.91% average differential per month was significant at the 5% level.

The authors posited that the source of the underperformance of liquidity in momentum sorts was due to the liquidity-momentum dynamics experienced by the loser portfolios. The study found that low volume losers tend to reverse at a faster rate than high volume losers, achieving more than 1% per month in all portfolio combinations while high volume losers tended to not show any signs of reversal over the 12 months post sort. Importantly, when considering longer investment horizons, the findings presented further evidence on the effects of liquidity on reversals. The authors found that high volume past winning shares tend to reverse sooner than low volume previous winners and conversely, low volume historical loser shares reverse faster than high volume historical losers. Using this finding, the authors implement two liquidity based momentum strategies where the first buys low volume winners and sells high volume losers, referred to as an *early stage* momentum strategy, and the second buys high volume winners and sells low volume losers, referred to as a *late stage* momentum strategy. Both strategies were then compared to a simple strategy (a conventional momentum strategy sorting only on cumulative return and not liquidity). The authors found that the *early* momentum strategy achieved the highest excess return 12 months post portfolio sort (15.03% per annum on average) and continued to produce positive excess returns up to 48 months post investment and only began to dissipate 60 months post investment. Conversely, the *late* momentum strategy achieved the lowest initial excess return of 7.14% per annum on average and experienced negative excess returns thereafter.

Grundy and Martin (2001) considered momentum on the cross section of shares listed on the NYSE and AMEX over the period August 1926 to July 1995. The authors showed that when considering the entire sample period, the mean monthly return of a six month estimation and holding period momentum strategy that buys past winners and sells past losers, assuming a 90th and 10th percentile split with a single month gap between portfolio formation and investment period, was 0.44% per month. The result is significantly lower the findings of Jegadeesh and Titman (1993) and the authors attributed the poor performance to a negative January effect over the initial part of the sample period. The mean return of the momentum strategy in Januaries across the sample period was -5.85% on average and was significant at the 5% level. In order to account for systematic risks, the authors considered two attribution models, where the first applied an equally weighted market proxy as well as an excess size factor as independent variables. The second attribution model was a Fama-French three factor model and therefore applied an equity market premium as well as size and value factors as independent variables. Using the first model, the authors calculated risk adjusted returns by first calculating the factor loadings for each

momentum portfolio over its respective formation period and then calculating excess returns earned over and above the attribution model. When applying and calculating risk-adjusted returns, the authors found that momentum profits were far more stable and significant over the sample period, achieving risk-adjusted returns of 1.34% per month and little to no January effect as 43 of the 69 Januaries displayed profitable momentum returns. Furthermore, the authors found that the application of risk models explained a significant amount variation in momentum returns, however, similar to Fama and French (1996), failed to explain the high level of average returns.

Jegadeesh and Titman (2001) re-examined momentum in share prices over an extended time period and increased the scope of the cross-section of shares in order to rebut the assertions of data mining. The revised sample considered all shares listed on the NYSE, AMEX and NASDAQ, increasing the universe beyond the NYSE and lengthening the original sample period by a further nine additional years. Using a six-month sorting and holding period, overlapping rolling portfolios were estimated assuming equally weighted average returns. The authors found that over the entire sample period, January 1965 to December 1998, a strategy of investing in previous winners and selling previous losers resulted in an excess abnormal return of 1.23% per month. Contrary to the notion of data mining, the authors found that in the most recent nine years post their original sample end date (out-of-sample), momentum profits were actually greater, producing a significant excess return of 1.42% per month. In order to strengthen the validity of the tests, the authors included the average return achieved by an equally weighted portfolio made up of every share considered within the universe examined. On average, the pure winner portfolios outperformed the equally weighted index by 0.56% per month, while loser portfolios underperformed the equally weighted index by 0.67% per month. Lastly, momentum strategies were conducted while simultaneously sorting on market capitalization based on the median market capitalization of the NYSE. The authors found that there is a significant momentum premium independent of size, yet, the excess returns seemed to be higher amongst the smaller capitalization shares.

Lewellen (2002) considered the sources of momentum profits on the cross-section of US shares and attempted to identify whether size, value or industry classifications explained the momentum phenomenon. The test included all shares listed on the NYSE, AMEX and NASDAQ over the period January 1941 to December 1999. As opposed to using the weighting mechanism proposed by Jegadeesh and Titman (1993) where zero cost strategies are formed by fictitiously longing the top 10% historical performers and simultaneously shorting the bottom 10% of shares based on historical cumulative returns, the author used a weighting strategy based on the shares cross-sectional cumulative market adjusted return. The weighting mechanism results in shares that achieved the highest historical returns achieving the largest weighting while shares with the lowest returns received negative weightings. Using pure momentum in share prices, value (proxied by BM), size and industry classifications, the study found that momentum profits achieved cumulative

profits from individual shares (pure momentum) of 3.55% per dollar long on an equally weighted basis (cumulative return over six months post sort) and 3.04% on a value weighted basis.

The results of momentum in industry portfolios was consistent with the findings of Moskowitz and Grinblatt (1999) where using a six month portfolio formation and holding period, industry momentum achieved significantly positive cumulative return per dollar invested of 3.65% (average cumulative return earned six months post sort). Furthermore, consistent with the findings of Jegadeesh and Titman (1993), the author found that both pure and industry momentum experience reversals between nine and 12 months post portfolio sort. Uniquely, when conducting dual sorts on value and size, momentum profits where in some instances stronger than pure momentum and industry sorts and were less likely to experience reversals in returns. Moreover, equal weighting always achieved higher returns than value weighted portfolio returns. When combining all three styles, using 25 size and BM sorted portfolios; the cumulative return six months post portfolio sort was 3.93% on an equally weighted basis and 3.23% when using value weighting.

Like Lewellen (2002), Jegadeesh and Titman (2002) utilized the weighting scheme proposed by Lo and MacKinlay (1990), referred to as the weighted relative strength strategy (WRSS). In order test the effect of the weighting schematic, test portfolios were formed using the cross-section of US shares listed on the NYSE and AMEX over the period January 1965 to December 1997. The mechanics of the WRSS differ to that of the conventional equally-weighted or value weighted portfolio methods used in previous studies. The WRSS results in a natural zero net investment strategy that assigns portfolio weights to each share based on the shares relative performance against the cross-sectional average performance of the universe of shares. This implies that the historical best winners are assigned the highest weights while the historical worst losers are assigned the lowest (negative) weights. The authors found that when using a WRSS weighting strategy, the long portion of the portfolios achieved excess returns of 8.12% per year (0.68% per month) on average. The purpose of the WRSS weighting method used by the authors was specifically to counter the argument proposed by Conrad and Kaul (1998), who hypothesized that momentum profits are directly related to cross-sectional variation in unconditional expected returns as opposed to time-series serial dependence in share returns. The core proposition of the study of Conrad and Kaul (1998) was that momentum profits are defined by average expected returns and therefore risk. Jegadeesh and Titman (2002) concluded their study by rejecting the findings of Conrad and Kaul (1998) in favor of behavioral drivers of momentum (time-series based expected returns) and importantly proved that momentum profits are present irrespective of the portfolio weighting mechanism used.

Lesmond, Schill and Zhou (2004) considered the effects of trading costs and other price frictions on momentum profits. The study considered all shares listed on the CRSP database over the

period January 1980 to December 1998. The methodology applied was marginally different to that of Jegadeesh and Titman (1993) as shares were sorted into one of three portfolios based on their historical six month cumulative returns while overlapping portfolio window periods were not used. Similar to the seminal work of Jegadeesh and Titman (1993), the authors did use a 10th, 90th percentile split and found that extreme winners outperformed extreme losers by 0.92% per month on average and was significant at the 5% level. The authors noted that the majority of the zero-cost trading strategy profits were earned from the fictitious short position in the loser portfolio. The authors found that when considering the extreme winner portfolios, the typical shar1e was high beta, small market capitalization and non-NYSE listed. Due to the nature of the typical winner share, specifically average size and illiquidity, such shares were suspected to be subject to larger scales of trading costs. In order to determine the effects of transactions costs, the authors used an indirect method of estimating transaction costs through a limited dependent variable (LDV) procedure described by Lesmond, Ogden and Trzcinka (1999). The authors found that when matching the transaction costs of applying a momentum strategy to the experiment, momentum is consumed by trading costs. Specifically, in aggregate, the winner minus loser strategy achieved net profits of 5.5% per half year, but generated combined costs of 13.6%. The authors concluded that the fictional trading cost of 1% applied by Jegadeesh and Titman (1993) significantly understated true transaction costs and as such, failed to consider the numerous sources of trading costs such as bid-ask spreads, taxes and short sale restrictions but most importantly, failed to consider the time variant nature of trading costs experienced across markets.

Korajczyk and Sadka (2004) explored whether momentum remains profitable after considering market frictions connected to trading. In order to focus on trading costs associated with implementable momentum strategies, the study limited empirical testing to long-only, winner based strategies, specifically 12 month and 6 month formation periods with 3 and 6 month holding periods allowing for a single month between the formation and investment period in order to account for microstructure effects. The study considered the cross-section of shares listed on the NYSE over the period February 1996 to December 1999. The authors found that both strategies achieved significantly positive returns over the risk-free rate and equally weighted market proxy, where the first strategy achieved raw returns of 1.71% and 2.13% per month on average assuming value and equal weighting, while the second strategy achieved long-only raw average returns of 1.49% and 1.93% per month. In order to determine the effects of transaction costs, a single momentum strategy was selected and returns net of transaction costs were calculated. The study considered two sets of transaction costs, the first being proportional transaction costs determined using the effective bid/ask spreads of shares in the underlying momentum portfolios and the second using non-proportional transaction costs related to the size of the underlying investment. The authors found that when considering proportional transaction costs, both momentum portfolios achieve significant risk-adjusted profits in terms of alphas, with the 12

month/ 3 month long only portfolio producing alphas of 0.61% and 0.45% per month on an equal and value weighted basis. In order to proxy for non-proportional price impact effects, the Breen, Hodrick and Korajczyk (2002) price impact model (BHK) and the Glosten and Harris (1988) price impact model (GH) were used. The authors found that when using the BHK model, abnormal momentum profits (assuming a value weighted strategy) are driven to zero as the underlying fund size exceeds $2 billion. Similarly, when using the GH model, alpha is driven to zero when the fund size exceeds $3 billion. Importantly, the assumption of equally weighted portfolio investments results in excess profits being reduced to zero well before the fund size reaches $1 billion for both strategies. The findings of the study are in fact two fold as proportional costs of trading do not seem to play a significant role in reducing momentum profits, however when considering non-proportional trading costs, equally-weighted momentum profits are severely compromised implying that equally weighted "paper" profits commonly described in literature may not be practically achievable.

Cooper, Gutierrez and Hameed (2004) considered the effects of market states on momentum over the sample period January 1926 to December 1995 and considered all NYSE and AMEX stocks listed on the CRSP monthly database. Using the conventional methodology of a six-month estimation period and a one-month lag between estimation and portfolio formation (in order to account for bid-ask bounce) momentum test portfolios were formed. The authors examined three momentum-holding periods of one, six, twelve months as well as a sixty-month period in order to test of reversal in momentum profits. In order to calculate risk-adjusted returns, the authors used both CAPM and Fama-French three factor time-series regressions in order to define factor loadings and calculated excess returns as the differential between actual returns versus returns defined by the predetermined factor loadings. Excess risk-adjusted returns where then cumulated in order to form holding period profits while two states of the market ("UP" and "DOWN") were defined using the historical 36 month return of the CRSP value weighted index.

The authors found that following an UP market, the mean monthly profit of the six month holding and estimation period momentum strategy achieved a raw monthly return of 0.93% per month, alpha of 1.12% per month when using the CAPM as the risk model, and an alpha of 1.28% per month when using a Fama-French three factor model, all of which were significant at the 1% level. Conversely, the authors found that when momentum strategies were applied following DOWN markets, momentum profits were largely obliterated, only achieving a negative raw return of -.037% per month, a CAPM driven alpha of 0.01% and a Fama-French alpha of 0.64%, both of which were statistically insignificant. The findings of the study therefore implied that momentum profits on the cross-section of shares listed in the US were inextricably linked to movement in the market, yet such findings were in direct contravention to those of Jegadeesh and Titman (1993, 2001) as variations in the market seemed to significantly drive momentum profits.

Chordia and Shivakumar (2006) attempted to determine the relationship between price and earnings momentum credited to Ball and Brown (1968). The study considered all shares listed on the NYSE, AMEX and NASDAQ over the sample period January 1972 to December 1999. Initially in order to create an earnings momentum factor excess return time-series, shares were initially sorted into deciles based on their standardized unexpected earnings (SUE) relative to their previous and latest earnings announcement. Portfolio holding periods were set to six months post formation and returns were equally weighted calculated assuming overlapping portfolio formation periods, consistent with the methodology employed by Jegadeesh and Titman (1993). Over the sample period, the top SUE portfolio achieved 1.68% per month while the excess portfolio returns of the top SUE less the bottom SUE portfolio achieved an excess return of 0.9% per month and was significant at the 1% level. Similarly, price momentum portfolios were formed assuming a six month formation and holding period and the average monthly excess return over the sample period was 0.76% per month and significant at the 1% level.

In order to determine whether either strategy could explain the other, the authors manipulated the Carhart (1997) model to incorporate either the excess return series of the earnings momentum or price momentum strategy when describing the other factor. Using the price .momentum portfolio returns as the dependent variable, time-series regressions were run using a variant of the Carhart (1997) model that supplemented earnings momentum as a priced factor. The results indicated that the earnings momentum factor managed to fully explain price momentum as alphas actually decreased when moving from the extreme loser to winner portfolios. Conversely, when applying the Carhart (1997) model to the earnings momentum portfolios, price momentum was unable to explain earnings momentum. In order to further test the effects of earnings momentum on price momentum, the authors constructed share-by-share cross-sectional regressions based on the methodology suggested by Brennan, Chordia and Subramanyam (1998). The authors found that the price momentum proxies were all originally significant, yet when including a proxy for historical earnings surprises, price momentum proxies were made redundant, therefore further confirming the time-series regression results and furthermore, that price momentum is merely a weak proxy for earnings momentum.

Sadka (2006) considered the effects of liquidity risk and the potential ability of liquidity explaining price and earnings momentum. Importantly, the study assumed that liquidity was separated into two components, namely *variable* and *fixed*. Emphasis was placed on variable liquidity, which by definition represents a market wide liquidity factor. Using only shares listed on the NYSE over the time-period January 1983 to August 2001, the study considered both intraday and monthly data. In order to determine the fixed and variable components of liquidity, the author utilized the model of Glosten and Harris (1998) to estimate the components of price-impact, which were directly related to liquidity measures. The model considered two trade variables, the first of which is a binary variable representing whether a trade is buyer or seller initiated and the second, an

interaction variable that combines the trade sign (determined by whether the trade is buyer or seller initiated) scaled by the value of the transaction. The coefficient of the first variable is the 'fixed' liquidity component and the second 'variable'. In order to determine the effects of the liquidity proxies on momentum, 25-price momentum portfolios were formed based on the historical cumulative 12-month return and held for six months post portfolio formation. Portfolios were sorted monthly and equally weighted overlapping portfolio returns were calculated over the sample period. The best performing historical winner shares achieved an average excess return of 1.44% per month while historical losers achieved -0.5% per month. The monthly return spread of winners minus losers was 1.93% per month on average and significant at the 1% level. Using cross-sectional regressions, the study tested the effects of including the fixed and variable liquidity measures by combining the liquidity factors with a CAPM specification as well as a Fama-French three factor model. In cross-sectional regression results, the variable component of market wide liquidity managed to explain more than 60% of the abnormal profit attributable to momentum, equating to 6.8% of the total annualized average profit in momentum being attributable to (variable) liquidity.

Rachev, Jasic, Stoyanov and Fabozzi (2007) considered a methodological variation in defining momentum using risk-reward criterion as a selection mechanism as opposed to cumulative returns. The study was conducted on the cross section of shares listed on the S&P 500 over the period January 1996 to December 2003. The selection/sorting criteria used in the study added a dimension to the conventional methodology applied to all prior studies of momentum. The authors considered three risk-return based criteria. Of the three, two account for the non-normality typically found in share returns, specifically the stable-tail adjusted return ratio (STARR) and Rachev-ratio, both of which assume non-normal stable Paretian distributions. The third risk-return criterion was the conventional Sharpe ratio, which assumes that share returns follow Gaussian (parametric) distributions. Using the conventional portfolio estimation and holding periods of six months, the authors found that the cumulative return stock selection criteria (as per Jegadeesh and Titman (1993, 2001) achieved the highest return of 1.28% per month, the R-ratio achieved a monthly return of 0.86% per month, the Sharpe ratio 0.65% per month and the worst performing measure was the STARR ratio, achieving an excess average monthly return of 0.61% per month. The results indicated that the commonly applied method to determining or sorting momentum portfolios achieved the highest level of returns in terms of economic magnitude. The study then considered the distributional properties of the momentum returns and evaluated the differing selection criterion methodologies by applying an independent risk-return measure. The authors found that even though the cumulative return criterion provided the highest realized return, the R-ratio selection criterion provided superior risk-adjusted performance and significantly lower tail risk. The authors concluded that the additional realized return attributable to using the cumulative

return selection criterion is compensation for the increased tail risk exposure borne from such a strategy.

Sagi and Seasholes (2007) considered the possibility of firm specific attributes explaining the momentum phenomenon. The firm specific attributes considered were growth prospects, costs and revenues. The data set analyzed contained quarterly revenues, costs of goods sold and book values of all shares listed on the CRSP database over the period of January 1963 to September 2004. In order to determine the effects of firm specific criterion, shares were initially sorted into quartiles on revenue growth volatility, cost of sales and market-to-book ratios (considered a proxy for firm growth options). A secondary conditional sort was then conducted where, within each quartile, shares were sorted into one of twenty portfolios based on the previous quarter's returns. Portfolio returns were then calculated on a value-weighted basis. When solely considering momentum in share prices, the top decile extreme winner shares outperformed the bottom decile extreme loser shares by 11.08% per annum with the difference being significant at the 1% level. The initial combination strategy was a dual sort on earnings/revenue volatility and momentum. In order to calculate a proxy for return volatility, annualized changes in revenues were calculated using the previous 10 revenue data points. When applied in combination, the highest revenue volatility portfolios produced the largest momentum profits, where excess returns were 13.26% per annum and significant at the 1% level. The second firm specific attribute analyzed was revenue costs and used costs of goods sold scaled by total assets as the initial sorting criterion. The authors found that excess returns seemed to be marginally stronger in the lower cost of sales shares as low costs shares achieved excess momentum profits of 8.14% per annum and were significant at the 5% level. When using the market-to-book ratio as a proxy for growth options, the findings indicated that growth options increase return autocorrelation as high market-t-book ratio firms achieved average excess momentum returns of 10.08% per annum and were significant at the 1% level. The findings provided evidence in favor of firm specific attributes contributing to increased autocorrelation in share returns and therefore indicating that firm specific attributes tend to explain a portion of the cross-sectional variation in momentum returns.

McLean (2010) attempted to link the persistence of momentum to idiosyncratic risk as idiosyncratic risk is considered a limitation to arbitrage, thereby removing the possibility of arbitrageurs trading away momentum. Per Pontiff (2006), arbitrageurs may be limited when engaging in style-based strategies due to the exposure to idiosyncratic risk, as idiosyncratic risk is seen to be a significant holding cost. Therefore, if a positive relationship between the stylistic investment strategy and idiosyncratic risk is found, the persistence of the strategy may be explained by idiosyncratic risk. The study considered all shares contained in the CRSP files (NYSE, AMEX and NASDAQ shares) over the period January 1965 to December 2004. In order to determine the effects of idiosyncratic risk on momentum profits, a number of differing weighting schemes were used and included equal weighting, value weighting, weighting according to

idiosyncratic risk and weighting according to the inverse of idiosyncratic risk. Momentum portfolios were calculated by sorting shares into quintiles using a six month portfolio formation and holding period where returns were calculated on an equally weighted basis assuming overlapping portfolio formation and estimation periods. Importantly, idiosyncratic risk is generally proxied by the univariate variance of the time-series in question, however, in the study, idiosyncratic risk was defined as the variance of portfolio returns orthogonal to the market proxy as well as the Fama-French three-factor model. In initial tests, the momentum sort achieved excess average returns of 0.74% and 0.88% per month (both significantly so) on an equally weighted and value-weighted basis. When weighting shares according to idiosyncratic risk, the momentum sort achieved excess returns of 0.375% per month and when using the inverse of idiosyncratic risk, excess returns were 0.716% per month. The result implied that momentum maintains a negative relationship with idiosyncratic risk as the highest (lowest) excess portfolio return and alpha was that of the inverse idiosyncratic risk weighted (idiosyncratic risk weighted) momentum portfolio. The results concluded that momentum profits cannot be explained by idiosyncratic risk being a limit to arbitrage as this would require a positive relationship between momentum and idiosyncratic risk.

Novy-Marx (2012) questioned whether momentum in share prices can actually be considered "momentum" and pays specific attention to the length of time prior to portfolio formation, referred to as the portfolio estimation period. The study covered all shares listed on the CRSP database (thereby including NYSE, AMEX and NASDAQ shares) over the period January 1926 to December 2010. The assertion of momentum not being true "momentum" is based on the timing and source of momentum profits. This would entail asking the research question pertaining to the estimation period; in a 12-month estimation period prior to portfolio formation, which portion contributes more to momentum profits? I.e. months 12 to 7 or months 6 to 2, referred to as the 'intermediate' and 'recent' horizon respectively. The author found that the former (months 12 to 7) are better predictors of momentum profits. In parametric tests, cross-sectional Fama-Macbeth style regressions were run on momentum-sorted portfolios where both the cumulative return between months 12-7 and months 6-2 are included. The results of the cross-sectional regressions indicate that the coefficient of the 'intermediate' horizon variable was economically twice the size of the 'recent' horizon variable and the difference is significant at the 5% level. A secondary set of non-parametric tests were performed, where rolling time-series regressions were applied to the two variant momentum strategies using 'intermediate' and 'recent' horizon estimation periods. The Fama-French three factor and Carhart four-factor model were used for the rolling time-series regressions. The results confirmed those of the parametric tests as the intermediate horizon portfolio (formed using months 12 to 7) achieved excess returns of 1.2% per month compared to the recent horizon portfolio, which achieved 0.67% per month. More importantly, the difference between the two strategies of 0.54% per month was significant at the 5% level.

Wahal and Yavuz (2013) considered the findings of Barberis and Shleifer (2003) regarding style investing and comovement between styles and individual assets that form part of the style portfolios. The study considered all shares listed on the NYSE, AMEX and NASDAQ over the period January 1965 to December 2009. In initial tests, the authors found that historical returns on size and value sorts (summarily referred to as “styles”) help to explain the cross-section of US share returns, even after controlling for size, value and momentum. The implication of the findings indicated that historical style returns do in fact add explanatory power and therefore justified the application of a measure of comovement being used as a descriptive variable. The authors conjectured that if style based investment generates asset level predictability and momentum (per Barberis and Shleifer (2003)) then the utilization of style comovement measures would result in a variation in momentum returns. The authors therefore conducted a dual sort on pure price momentum per Jegadeesh and Titman (1993, 2001).

The authors used the popularized portfolio momentum methodology assuming a six-month estimation and portfolio-holding period. The secondary sort on style comovement was done on each share where daily share returns were regressed on daily style returns over the previous 3 months. Comovement beta estimations were conducted monthly resulting in each share having time-series comovement betas over the sample period. The two-way portfolio sort was conducted independently where shares were sorted into deciles based on price momentum and terciles based on style comovement. Portfolios were sorted monthly and overlapping equally weighted portfolio returns were calculated over the sample period as done by Jegadeesh and Titman (1993, 2001). The findings regarding the dual sort were consistent across all performance measures used, specifically raw returns and regression alphas. Portfolio returns increased monotonically as style comovement increased. Excess returns on portfolio sorts increased from 0.71% per month in the low comovement sort to 1.15% per month in the high comovement style portfolio, where the difference in portfolio returns was significant at the 5% level.

Like Cooper, Gutierrez and Hameed (2004), Hammami (2013) considered the effect of the prevailing economic state on momentum profits. The study considered the cross-section of US shares (NYSE, AMEX and NASDAQ) over the sample period January 1927 to December 2009. In order to separate the effects of size, portfolios were sorted independently on size and momentum, where momentum sorts were based on the historical 11-month continuously compounded return, allowing for a one-month gap between estimation and investment. Portfolios were sorted and formed monthly and overlapping equally weighted size neutral momentum returns were calculated over the sample period. Regression analysis was used in order to split the sample period into varying economic states, where the equity market risk-premium (“EMRP” hereafter) was estimated using lagged variables of dividend yield, term spread, default spread and Treasury bill rate. The regression coefficients were then used to determine the EMRP and EMRP was then compared to its historical median value. The months were then stratified into

'good' and 'bad' times where 'good' implied that the EMRP was below its historical premium, while 'bad' was the inverse. The logic behind the stratification was based on relative risk-aversion dictated by the market risk-premium, where a historically higher premium implies increased relative risk aversion and therefore economically negative, high-risk aversion states. In order to determine the effects of the economic state on momentum profits, the sample period was split into three sub samples (1927-2009, 1927-1963, 1964-2009) and momentum profits were estimated over the full sub-samples, as well as in economic up and down turns.

Considering the full and sub periods, overall momentum profits were consistent, achieving 0.7% per month on average and were significant at the 5% level. However, momentum profits experienced significant variation when comparing good and bad economic states. In good economic times, momentum profits were significant, achieving 0.89% per month and were significant at the 1% level. Moreover, the standard deviation was lower than the full sample momentum excess return, implying that Sharpe ratios in good economic times were superior. Considering the 'bad' economic states, momentum profits were lowest, achieving excess return of 0.51% per month and just made significance at the 10% level. Consistent with the findings of Cooper, Gutierrez and Hameed (2004), the study provided evidence in favor of momentum being a market inefficiency or mispricing that primarily emerged in good times, negating the ability of parametric risk explaining the momentum phenomenon.

2.2.2 International evidence of momentum in share prices (Excluding the United States)

Rouwenhorst (1998) is credited with the first study of international momentum on a share-by-share basis outside of the United States. As stated by the author, the majority of evidence in favor of medium term momentum was conducted on virtually identical data sets of US shares between the 1920's and 1980's. By extending the scope of test to international markets, the study intended to examine whether medium term momentum in share prices is a global phenomenon that extended beyond the United States. The sample considered 12 geographically different European stock exchanges over the period 1978 to 1995 and in total included a sample of 2190 shares. Importantly, for each of the exchanges included, on average, the stocks analyzed made up 90% of the total respective exchanges market capitalization, implying a highly liquid tradable cross-section of shares. The sorting procedure applied was identical to that of Jegadeesh and Titman (1993) where at the end of each month, stocks with at least 12 months of historical returns were ranked based on four formation criteria (3, 6, 9 and 12 months) and sorted into decile test portfolios. Portfolios were then held for a varying number of holding periods identical to the formation periods used for share evaluation. Like Jegadeesh and Titman (1993), portfolios were allowed to overlap and returns were calculated on an equally weighted basis. The results of the initial sort were consistent with studies that limited testing to the US universe of shares. For all

variations of estimation and holding periods, the extreme winner portfolios significantly outperformed their extreme loser counterparts by approximately 1% per month.

In order to determine the effects of market beta, size and idiosyncratic risk, the author considered the six month estimation and holding period momentum strategy and found that neither size, market beta nor idiosyncratic risk explained the variation in returns for the ten test momentum portfolios sorted using the entire cross-section of European shares. In order to determine whether the momentum profits were not attributable to only a subset of indices within the combined sample of European shares as well as variation in market size of the different markets considered, momentum portfolios were constructed on a country-by-country and market capitalization basis. On a country neutral basis, 11 of the 12 countries displayed significant momentum profits and on average, country neutral portfolios produced excess momentum profits of 0.93% per month and were significant at the 1% level. In order to truly control for size, the author first constructed 10 portfolios based on market capitalization and then within each portfolio formed momentum portfolios based on historical returns. The results indicated that irrespective of market capitalization, momentum profits were significantly positive.

Notably, the study found a negative interaction between size and momentum as momentum profits decreased monotonically when moving from the small capitalization to large capitalization momentum portfolios. In order to calculate the effects of risk on the international momentum portfolios, the author conducted time-series regressions using the excess returns of each momentum portfolio over the German risk free rate, the excess returns on the Morgan Stanley Composite Index and the small minus big excess return portfolio calculated using the entire cross-section of shares considered. The author found that market betas for the extreme winner and loser portfolios were highly similar and the factor loadings on the size factor were similar. Importantly, and consistent with evidence from the US, the pure market model depicted significant alphas where winner portfolios achieved risk-adjusted excess return of 0.8% per month compared to -0.2% per month earned by losers. However, when including the size factor within the regression specification, the winner alpha decreased marginally to 0.5% per month while the loser portfolio dropped further to -0.9% per month, thereby providing additional proof of the negative interaction between momentum and size.

The final aspect of the study considered the relationship between US and European momentum profits. In pure correlation tests over the period 1980 to 1995, the correlation coefficient was 0.43, indicating positive relationship between both forms of momentum. A further test was conducted where European momentum returns were regressed on US momentum returns. The results of the regression indicated a significant US momentum coefficient, however the European momentum alpha was highly significant indicating that US momentum fails to wholly explain European momentum, indicating an element of independence and therefore inconclusive proof

of a global momentum premium. Importantly, the core findings of the seminal work showed that momentum was present on a global scale and not simply an elaborate case of data snooping on the cross-section of US shares. However, the findings found weak evidence in favor of a global momentum factor, implying that behavioral explanations of the momentum premium were a superior alternative in explaining the momentum phenomenon.

Rouwenhorst (1999) extended the international momentum literature to consider emerging foreign economies, therefore adding a dimension to the seminal work of momentum profits in international markets. Emerging markets are considered more segmented and therefore are less likely to conform to global factors that are correlated with the cross-section of share returns. The analysis of emerging markets strengthens the power of the test relating to the identification of factor premia explaining share returns, specifically momentum in share prices over the medium term. The study considered the effects of size, value, momentum and liquidity using 20 emerging markets over the sample period January 1982 to December 1997. In order to study the local return factors in emerging markets, portfolios were sorted monthly on beta, historical cumulative six-month returns, BM ratio and turnover. All portfolio returns were calculated on an equally weighted dollar basis. The findings pertaining to momentum showed that historical winner shares outperformed historical losers in 17 of the 20 countries analyzed. When implemented across the total sample of 20 countries, the excess zero cost return strategy achieved excess returns of 0.39% per month, significant at the 5% level.

Interestingly, the correlation between momentum returns across the various emerging markets averaged -0.007, indicating that momentum profits were independently present but lacked a commonality across the various exchanges. The findings of the paper provided powerful insight into momentum mechanics within emerging markets, where momentum profits within emerging markets seemed to be qualitatively similar to those found in the US and Europe (winners outperformed losers) but were economically smaller (0.39% excess average monthly return compared to approximately 1% per month). Furthermore, the minimal correlation in momentum returns across markets seemed to negate the hypothesis of a global momentum premium present over differing markets, implying a less plausible argument for momentum being a priced global systematic factor.

Hameed and Kusnadi (2002) considered the profitability of momentum strategies in emerging markets, specifically equity markets within the Asia Pacific basin over the period January 1979 to December 1994. The authors conjectured that the analysis of emerging markets allows for the validation of theories explaining the source of momentum profits (a deeper discussion of the varying theories attempting to define the source of momentum profits will be conducted in the next section). Behavioral theories unanimously attribute momentum profits to under reaction by market participants regarding information. The low correlation between emerging and developed

markets implies that the identification of momentum is proof in favor of behavioral explanations of momentum, as risk based theories implicitly dictate a global systematic momentum premium. The authors considered six Asian markets using monthly stock returns (expressed in US dollars) of over 1000 individual shares listed over the period 1979 to 1994.

The study utilized the methodology employed by Jegadeesh and Titman (1993) where shares were ranked monthly based on their cumulative excess returns calculated over the prior 3, 6, 9 and 12 month estimation periods. Shares were then sorted into decile test portfolios and held for varying holding periods equal to the estimation period windows. Portfolios were constructed to allow for overlapping portfolio formation and estimation periods and returns were calculated on an equally weighted basis. When considering all six exchanges, the six-month estimation and holding period excess return portfolio achieved 0.53% per month, yet the return was not statistically significant. Importantly, all variations of the 16 momentum portfolios produced positive excess returns, however unlike the evidence of momentum profits in the US and Europe, none were statistically significant. In order to account for the effect of outliers, the authors resorted portfolios using 30th /60th percentile split, creating three test portfolios as opposed to decile portfolios. Consistent with the initial findings, even when using a simpler portfolio split, winner minus loser portfolios still produced positive, yet insignificant, momentum returns. Similar to the methodology of Rouwenhorst (1998), portfolios were sorted simultaneously on size, country and turnover.

The purpose of the dual sorting allowed for the momentum effect to be analyzed and simultaneously neutralizing the effects of size, liquidity and the possible lack of industry diversification caused by pooling the sample of shares. The results of the country neutral portfolio momentum sorts resulted in excess monthly returns of 0.37% per month and were statistically significant. Notably, the country neutral equally weighted zero cost momentum strategy achieved a standard deviation in monthly returns of 0.2% compared to 0.7% achieved by the pooled sample momentum strategy, providing proof of the lack of diversification experienced when not neutralizing country effects. In order to neutralize the effects of size on momentum returns, portfolios were formed first by sorting all shares into three size portfolio and then sorting on excess historical cumulative returns within each size tercile. Consistent with the results of Rouwenhorst (1998), momentum profits were strongest in the smallest size tercile, where excess returns were 1.21% per month and significant at the 1% level. Lastly, the authors then considered the effects of liquidity (proxied by turnover) and momentum profits. Shares were initially sorted into tercile turnover portfolios and then on momentum based on historical cumulative excess return. Of the three turnover portfolios, only the largest turnover group achieved a positive excess return of 1.12% per month and was significant at the 5% level.

Chan, Hameed and Tong (2000) extended the analysis conducted by Asness, Liew and Stevens (1997) and tested the presence of momentum on 23 foreign market indices, including Europe, Asia, Africa and the Americas, over the period January 1980 to June 1995. The study differed to that of Rouwenhorst (1998, 1999) as the authors considered momentum at index level as opposed to a share-by-share basis. Evidence of momentum at an index level would further provide proof of a pervasive momentum factor that is found across shares and indices globally. All returns were calculated in US dollar terms on a weekly basis. Initially, the full sample of country indices were used to calculate momentum profits over five differing estimation and holding periods ranging from one to 26 weeks. Notably, the authors used the weighting mechanism prescribed by Lo and Mackinlay (1990) and Conrad and Kaul (1993), where weightings were solely based on the relative cross-sectional outperformance (underperformance) of shares (or indices) at each sorting period.

The authors found that only the 12 week holding period produced statistically insignificant excess returns while the 4-week holding period excess return was 0.253% per week, equating to a statistically significant 1% per month. In order to account for risk, momentum profits were adjusted for world beta risk (implying the validity of a global CAPM). Momentum profits for each of the strategies considered were regressed on the excess world market return, where the estimated alphas of the time-regressions measured abnormal profits attributable to each index level momentum strategy. After adjusting for market risk, only the two and four week holding periods produce significant alphas, indicating that market risk is capable of describing momentum profits at very short and extended holding periods, but not in the medium term. In order to identify the effects of market capitalization on momentum returns, market capitalization weighted momentum profits were estimated over the full sample period. The results of the value-weighted sort indicated that for all holding periods, momentum profits decreased, but consistent with the equally weighted returns, the one and four week holding periods produced the highest momentum profits but decreased thereafter.

Lastly, in order to identify the effects of liquidity on momentum profits, the authors regressed the lagged trading volume over the previous *t-1* and *t-2* periods on current momentum *(t)*. The authors found that, barring the 26-week holding period, momentum profits maintained a positive relationship with lagged volume, implying that price continuation is stronger following increases in liquidity consistent with herding behavior theory. The results of momentum index profits differed from the evidence provided on a share-by-share basis. Firstly, adjusting for market risk negatively affected momentum alphas on an index level yet on a share by share basis, momentum profits were impervious to market risk adjustments (Jegadeesh and Titman (1993, 2001), Fama and French (1996)). Additionally, a number of studies had found that share by share momentum and liquidity maintain a negative relationship (Campbell, Grossman and Wang (1993)). Both findings

indicate that even though the presence of momentum profits at an index level is plausible and possible, the dynamics of the index momentum differ to that of share-by-share momentum.

Chui, Titman and Wei (2000) tested for the presence of momentum on the cross-section of shares across eight Asian markets over the sample period January 1970 to February 2000. The authors emphasized the differences between their data and that used by Rouwenhorst (1999) in terms of the larger scope of shares analyzed as shares were not pre-excluded based on market capitalization or liquidity as well as the sample period being significantly longer. Using the entire universe of shares, momentum portfolios were formed using overlapping six-month estimation and holding periods. In contrast to Jegadeesh and Titman (1993) and Rouwenhorst (1998), portfolio returns were value weighted in order to mitigate the effects of illiquidity while tercile, as opposed to decile, portfolio breakpoints were applied at each portfolio sort. When considering the entire sample of shares covering all eight exchanges, momentum profits were positive, achieving average excess monthly returns of 0.38% per month but were statistically insignificant.

Interestingly, when Japan was excluded from the universe of shares, excess momentum profits were over 1% per month and statistically significant at the 5% level. In order to remove country specific effects from momentum profits, country neutral portfolios were formed where portfolios were sorted in each of the specific countries analyzed. The value weighted country specific momentum portfolios were then combined on an equally weighted basis to form a single country neutral momentum strategy. The country neutral excess returns were lower than the full sample excess momentum returns (both including and excluding Japan) achieving 0.34% per month and lacking statistical significance. In order to test whether momentum profits within Asian markets conformed to behavioral theories that explain the momentum anomaly, the authors extended the test to allow for longer portfolio holding periods in order to test for reversal in momentum profits. Using both full sample and country neutral portfolios, momentum profits tended to continue up until nine months post portfolio formation but began to reverse from 10 months onward where from months 10 to 12, average excess monthly returns were -0.69% (full sample) and -0.36% (country neutral) per month on average.

In order to test the interaction between momentum and other style anomalies in the markets considered, dual sorts were conducted using value proxied by the book-to-market ratio, size proxied by market capitalization and liquidity proxied by turnover. When conducting country neutral dual sorts on size and momentum, a weak negative relationship emerged between firm size and momentum (as seen in the US) with the momentum spread between small and large firms being an insignificant 2.88% per year.

When conducting dual sorts on book-to-market and momentum, momentum profits were more prominent in low book to market (growth) shares, where the momentum spread between growth

and value shares was approximately 3.96% per year and significant at the 5% level. The study then considered the relationship between liquidity and momentum. In five of the eight countries analyzed, momentum profits were higher in shares that displayed higher levels of relative liquidity. The effects of liquidity on momentum profits was more pervasive when compared to the other styles used in dual sorts as the momentum spread between high and low liquidity was between 4% and 5% per year and was statistically significant at the 5% level. Lastly, the authors considered the effects of ownership structure on momentum profits. The study classified ownership structure based on levels of independence. The authors found that a positive relationship emerged between the degree of independence and excess momentum profits. In order to mitigate the effects of size on the results (independent companies where notably larger on average), momentum portfolios were sorted on size and ownership structure independently. The results of the three way sort further proved the notion that independent firms achieved higher momentum returns (approximately 2.1% per year) than firms with group affiliations, even when holding size constant.

Griffin, Ji and Martin (2003) attempted to identify whether macro-economic variables are able to explain the global momentum phenomenon. The study considered momentum profits estimated across 40 international equity exchanges over the sample period January 1975 to December 2000. Momentum portfolios were formed using the commonly reported six-month estimation and holding period strategy, where shares were sorted based on the 20th and 80th percentiles into winner and loser portfolios. Portfolios were sorted monthly allowing for portfolio estimation and holding periods to overlap while returns were calculated on an equally weighted basis. In order to avoid microstructure issues, a month gap was applied between portfolio estimation and formation. Uniquely, all portfolio returns were expressed in local currency terms, differing from previous literature that examined international momentum.

The initial findings were that within the sample of 40 countries, all African countries, 5 of 6 American countries, 10 of 14 Asian countries and 14 of 17 European countries displayed significant momentum. When considering regional momentum, Africa produced the largest momentum profits of 1.63% per month (significant at the 1% level) while Asia produced the lowest momentum profits of 0.32% per month and were not statistically significant. The study then attempted to test whether a risked based explanation of momentum was feasible by estimating correlations between each of the momentum excess return series. The purpose of the test intended to determine whether momentum is a systematically priced risk factor. The presence of significant cross-border correlation between country specific momentum excess returns would provide evidence in favor of a risk based explanation of momentum. Initially, correlations on a regional scale were analyzed (due to the size of the United States and Japan, they were considered their own regions). The highest average monthly correlation was between the United States and Europe, achieving a correlation coefficient of 13.9%. Considering all regions, the

average correlation coefficient was a meagre 3.2%, while interregional correlations were 10.3%. In order to gauge the intra and interregional cross-correlations, the authors conducted the identical correlation tests on regional and country index returns. The intraregional test using pure overall equity returns produced an average correlation of 33% while interregional produced a correlation coefficient of 47%.

The results of the correlation tests seemed to prove that momentum, as a risk factor, is not globally priced. In order to truly test whether global momentum profits are compensation for risk, the authors employed two risk-based models per Chen, Roll and Ross (1986) and Chordia and Shivankumar (2002). In order to test whether momentum profits were globally driven by unconditional macro-economic factors, in each country considered, four of the Chen *et al.* (1986) factors were estimated and Fama-Macbeth, two pass regressions were run and APT style models were used to calculate expected momentum returns. The authors found that actual momentum returns globally were approximately 0.67% per month on average, while the APT model predicted returns of -0.03% per month. The average difference of 0.7% was significant at the 5% level, showing that an unconditional APT model failed to explain global momentum profits over the sample period. The study then turned to using a conditional model based on the evidence presented by Chordia and Shivakumar (2002) where momentum profits were explained by the one month step ahead forecasts model that used a macro-economic factors as well as dividend yield of the overall market. The authors found that the conditional model significantly underestimated the momentum effects. The results of the correlations as well as the conditional and unconditional tests indicated that macro-economic risk factors failed to explain international momentum profits, reducing the plausibility of a risk-based explanation of international momentum.

Glaser and Weber (2003) considered the interaction between momentum and turnover on the Frankfurt Stock Exchange over the period June 1988 to July 2001. The authors considered 446 shares listed in the top market capitalization segment of the exchange. Momentum portfolios were constructed in accordance with Jegadeesh and Titman (1993) where, in each month over the sample period, shares were ranked on their cumulative raw returns over four estimation periods equal to 3, 6, 9 and 12 months. Shares were then sorted into one of five equally weighted portfolios and held for four-window holding periods equal in length to the estimation periods used for sorting purposes. In order to determine the effects of liquidity, shares were then independently sorted into one of three portfolios based on average daily turnover measured over the previous estimation period window months. Stocks were then grouped into one of fifteen portfolios based on momentum and turnover. The results of the portfolio sorts were consistent with international literature as all zero cost momentum strategies produced positive returns, achieving significant average excess returns of 0.96% per month. The results of the bivariate sorts indicated that momentum profits on the German stock market were significantly higher in shares with higher

turnover ratios. The results were consistent with those of Lee and Swaminathan (2000) who found a similar interaction on the cross-section of US shares.

The excess returns earned by high turnover excess momentum return portfolios was always greater than the low turnover excess momentum returns and significantly so in more than 80% of the simulations conducted. Interestingly, the authors found that the main contributor to the significant outperformance was on the part of winning shares. Considering the six-month holding and estimation period, the high turnover winner portfolio outperformed its low turnover counterpart by 0.78% per month and the difference was significant at the 5% level. This result contradicted the findings of Lee and Swaminathan (2000) as they found that the positive relationship between momentum and turnover was largely due to high turnover loser shares earning significantly lower returns than low turnover losers. In order to control for effects of industry, size and value, returns were adjusted using these factors and then sorted using the adjusted returns. The adjustment required that shares were grouped into one of 10 portfolios based on either size, book-to-market or industry classification. Returns were then adjusted by subtracting the specific share return by its classification portfolio return. The authors found that even when applying adjustments for size, value and industry, higher turnover momentum shares produced returns in excess of their lower turnover counterparts. Interestingly, when considering size, the results indicated that the positive relationship between momentum and turnover was largely driven by the mid-sized shares.

Moreover, the positive link between momentum and turnover disappeared in the top and bottom size tercile. In order to determine whether momentum returns were affected by seasonality, the authors conducted time-series regressions that used dummy variables as month proxies. The results indicated that momentum profits were generally lower in January while Loser shares experience the worst performance in the last three months of each year. The authors concluded that their results were probably best described by a behavioral model yet the viability of implementing a momentum strategy on the Frankfurt stock exchange was limited by the fact that momentum in high turnover stocks was less applicable to the large market capitalization tradable shares.

Hon and Tonks (2003) examined the profitability of momentum strategies on the cross-section of shares listed in the UK over the period January 1955 to December 1996. The study expanded both the time frame and cross-section of shares compared to Liu, Strong and Xu (1999), who found that over the period January 1977 to December 1996, momentum strategies yielded significant profits and were robust even when controlling for market risk, size, price and two proxies of value. Using the methodologies of De Bondt and Thaler (1985, 1987) and Jegadeesh and Titman (1993), portfolios were sorted using estimation and holding windows varying between 3 and 24 months, resulting in a total of 8 estimation and holding periods and 64 test portfolios. Notably different to other international studies, the authors used non-overlapping equally

weighted portfolio returns, resulting in a maximum number of 64 iterations being repeated over the sample period.

Like Jegadeesh and Titman (1993), shares were sorted into one of 10 portfolios based on their historical cumulative return. Considering the entire sample period, most of the 64 momentum strategy excess returns were positive while 24 of the strategies were significantly positive. The most profitable strategy was that of the 12 month estimation and six month holding period, receiving an annualized excess return of 16.2%. Furthermore, confirming the results of Debondt and Thaler (1985, 1987), the 3 month estimation and holding period portfolio achieved significantly negative returns, while all the 24 month estimation period strategies achieved excess returns that were not significantly different from zero. In order to test the findings of Liu *et al.* (1999), specifically whether momentum was a feature of the UK market, the authors split the sample period into two subsamples, the first considering the period January 1955 to December 1976 and the second, the latter half of the sample identical to the sample period analyzed by Liu *et al.* (1999).

The results of the first half of the sample differed significantly to that of the full sample. Of the 64 excess return strategies, most were positive but insignificant. Consistent with the findings of Liu *et al.* (1999), the momentum phenomenon seemed significantly pronounced over the latter half of the sample period where excess momentum returns were both positive and highly significant. Moreover, reversal only seemed to become apparent at the extreme end of the investment horizon windows, specifically after the holding periods were increased beyond 21 months. In order to determine whether momentum profits were associated with market risk, the market betas for each of the extreme portfolios were measured. The authors found that market betas of the loser portfolios were generally higher than those of the winner portfolios but the difference in betas was not statistically significant. The authors then considered whether the size effect, documented by Banz (1981), was responsible for the profits generated by the momentum strategy. When analyzing the average market capitalization in each of the extreme portfolios, the average size of loser portfolios was consistently and significantly (statistically) lower than their winner counterparts. Therefore, the presence of momentum on the UK stock market was not attributable to size nor market risk, however, the presence of momentum was disputable and largely not present over the period January 1955 to December 1976.

L'Her, Masmoudi and Suret (2004) examined the feasibility of a four factor pricing model, inspired by Carhart (1997), on the cross-section of shares listed on the Canadian stock exchange over the period July 1960 to April 2001. In order to identify whether momentum was present on the Canadian Stock exchange, the authors' use a $70^{th}/30^{th}$ portfolio split, where shares were sorted based on their historical cumulative return over the prior 12 months and held for the identical length window period. Like Jegadeesh and Titman (1993, 2001) the authors allowed for a one

month gap between portfolio estimation and construction in order to remove potential microstructure effects, bid/ask bounce and short term reversal. Over the sample period, excess momentum returns were extremely large and significant, achieving 16.07% per year (1.34% per month) and was significant at the 1% level.

Importantly, the correlation structure of the excess return premia (size, value and momentum) indicated that each of the factors considered where potentially orthogonal to asset prices. The study then extended to the testing of whether premia returns in the Canadian stock market were related to calendar effects. Jegadeesh and Titman (2001) noted a strong January effect in momentum returns while De Bondt and Thaler (1985, 1987) found that loser shares tended to outperform significantly in January. Considering the cross-section of Canadian shares, excess returns on the momentum portfolio were significantly positive in every month, barring January. In order to identify the performance of momentum in both up and down markets, the entire sample was stratified into up and down states. Over the sample period, excess momentum returns achieved positive average monthly returns in an up-state of 1.57% per month (18.88% annualized) while in market down states achieved 1.05% (12.63% annualized), both significant at the 1% level.

The results showed that momentum profits did not seem to be sensitive to extreme market movements. Lastly, the authors considered the effects of monetary policy on the factors analyzed where the sample was stratified into expansive and restrictive monetary policy periods using the current bank rate relative to the trailing 12 month average as a determinant. Notably, during restrictive monetary policy periods, momentum excess returns were significantly higher than expansionary periods, achieving 1.61% per month compared to 1.04% per month, implying that a market wide liquidity macro-economic factor failed to explain momentum on the Canadian stock exchange.

Demir, Muthuswamy and Walter (2004) investigated the presence of momentum in medium term stock returns on the Australian Stock Exchange. The study considered all approved securities on the Australian Stock Exchange over the period September 1990 to July 2001 as well as shares included in the All Ordinaries index over the period July 1996 to July 2001. The specific universe of shares used in the study were shares that carried the lowest trading cost and were least likely to incur significant shorting costs. The authors noted that International studies of momentum were highly dependent on the shorting of loser shares, therefore the universe constraints allowed for a more realistic study of momentum. Further, most studies historically used a single month between portfolio estimation and investment in order to mitigate the effects of micro-structure issues and short-term reversal. The authors considered a more granular approach and used the volume weighted average price as opposed to ruling bid/ask prices that would result in a similar effect. Consistent with the methodology applied by Jegadeesh and Titman (1993), shares were sorted

on their previous 30, 60, 90 and 180 day cumulative excess returns and sorted into deciles and held for identical periods used for estimation. Portfolio returns were equally weighted while three return scenarios were applied, namely buy-and-hold, arithmetic and logarithmic returns.

The results of the initial momentum sort found that all the simulations produced positive returns. The best performing strategy was the 180/30 day simulation while the inverse was the worst performing with the former achieving excess returns of 5.34% per month, while the latter 1.38% per month. This entailed that the worst strategy was effectively equivalent to the best performing US momentum strategy, while the best portfolio achieved excess returns almost five times greater than the 1% per month documented in international momentum literature. Moreover, the study found no evidence of the one-month reversal noted by Jegadeesh (1990) and Lehmann (1990). In order to determine the effects of size and liquidity, simulations were rerun allowing for variation in size and cumulative excess returns independently as portfolios were sorted on historical cumulative excess return over the previous 30, 60, 90 and 180 days and simultaneously sorting shares into one of four size portfolios based on market capitalization at the end of the estimation period. The authors found that 15 of the 16 size quartiles resulted in significant momentum returns barring the largest quartile 30 day estimation and holding period portfolio simulation. Consistent with international literature, momentum returns exhibited a negative relationship with size, with the lowest market capitalization stratum delivering the highest momentum portfolio returns. Importantly, when statistically comparing the smallest quintile momentum profits with the largest quintile, only 5 of the 16 simulations were statistically significant, indicating that larger shares still exhibited significant momentum.

In order to further test the robustness of the results, portfolios were sorted simultaneously on momentum and liquidity, where liquidity was proxied by average daily trading volume. The authors found that of the 64 momentum-liquidity simulations, 63 achieved positive excess returns that were significant at the 1% level. Contrary to international findings, momentum excess returns seemed to maintain a negative relationship with average daily trading volume, where the least liquid portfolios consistently achieved higher excess returns over the larger liquidity shares. Lastly, the final robustness considered the risk-adjusted returns of the momentum portfolios. Risk adjusted returns were calculated using a market model to define excess momentum profits. The findings indicated that risk-adjustment had little effect on momentum profits, as all of the excess momentum returns for all 16 simulations were significant at the 1% level. The findings therefore indicated that momentum profits on the ASX were significant and not explained by size, liquidity or risk-adjustment. More importantly, momentum profits were consistently and significantly higher than those found in other international studies.

Griffin, Ji and Martin (2005) attempted to extend the international evidence of price and earnings momentum by testing price and earnings momentum strategies in 40 and 34 international markets

respectively, over the sample period January 1975 to December 2000. For the price momentum strategies, the conventional six month estimation and holding period momentum strategy was used, allowing for a month gap between ranking and investment periods in order to mitigate microstructure effects. Portfolios were formed on a monthly basis, therefore allowing overlapping portfolio investing and estimation periods. In order to sort shares using earnings momentum, shares were ranked monthly using their consensus one year earnings forecast scaled by price. All portfolios were sorted using the two momentum proxies using an 80th / 20th percentile split, as decile sorting was not feasible due to the limited number of shares and low liquidity levels in some of the developed markets considered.

The findings indicated that both price and earnings momentum excess returns were largely profitable in all the countries considered. In line with prior literature, price and earnings momentum profits in Asia were lower when compared to the other markets considered. In terms of price momentum, 34 of the 40 markets considered displayed statistically significant price momentum, while 27 of the 34 markets displayed significant earnings momentum. In order to limit the noise in single market momentum strategies, momentum profits were equally weighted in order to determine regional momentum profits. The price momentum regional results indicated that Africa experienced the highest momentum profits of 19.62% per annum, the America's achieving 9.41%, 9.21% achieved by Europe and lastly 3.83% achieved by Asia. In order to determine the interaction between earnings and price momentum, two independent sorts were conducted were portfolios were sorted initially based on price momentum (earnings momentum) and within the price (earnings) momentum groups, shares were sorted on earning (price) momentum.

The result was dual independent sorts allowing for variation in both earnings and price momentum. When conducting the initial sort on earnings momentum, within group price momentum was significantly positive in all the American markets and all but one European market while only five of the 13 Asian markets achieved positive 'in group' price momentum. Similarly, when conducting initial sorts on price momentum, earnings momentum was consistent and positive within the price momentum groups for the majority of markets considered. The results indicated that globally, price and earnings momentum were independent factors, and therefore separate and profitable phenomena. A final test was conducted that utilized both earnings and price momentum in a single strategy where shares were sorted simultaneously on price and earnings momentum. The results showed that the combined sorts were far more profitable than the pure earning/price momentum sorts, further strengthening the evidence in favor of price and earnings momentum being independent global pricing anomalies.

Fong, Wong and Lean (2005) applied a stochastic dominance approach to evaluate international momentum strategies. Stochastic dominance theory was used as the preferred evaluative method as the basis for stochastic dominance allows for laxities in the assumptions governing choice

under risk and the distribution properties of returns. The common focus in stochastic dominance analysis is related to the order, namely first, second and third order stochastic dominance (but focused on second and third order as is done in literature). The study considered 24 international indices covered by the Morgan Stanley Capital International over the sample period January 1989 to December 2001, where both developed and developing markets were considered. Following the methodology of Jegadeesh and Titman (1993), markets were sorted based on their 1,3,6,9, and 12 month historical cumulative returns. Indices were then sorted into one of six portfolios and held for identical window investment periods and geometric returns were calculated assuming equal weighting. The authors found that over the sample period, momentum profits were significantly positive and high, achieving approximately 4% per month on average when considering the entire sample of country indexes considered.

In order to determine the persistence of momentum, the sample period was split into two sub-periods where the first related to the period January 1989 to December 1996. Over the period, 22 of the 24 indices achieved significantly positive momentum profits. The latter sub-period between January 1997 and December 2001 was considerably more bearish and volatile as only 16 of the 24 indices achieved positive excess momentum returns, of which only 8 were statistically significant. In order to determine the source of momentum profits, stochastic dominance tests were applied by testing the first and second order dominance of the winner and loser portfolios. The results of the stochastic dominance tests indicated that winners stochastically dominated losers at the second and third levels implying that winner portfolios were more predictable to investors, garnered less risk when compared to losers and that momentum returns are consistently more positively skewed, indicating that winners would be a natural choice for any risk-averse utility maximizing investor. The results were in favor of a behavioral explanation of momentum as opposed to a risk based one, with momentum in international indices over the sample period being driven by herding behavior.

Wang (2008) considered the profitability of momentum strategies in the United Kingdom, Germany, Japan and China over the period January 1991 to December 2006. A series of filters were applied to the data where the first months return was deleted in order to eliminate the effects of listing underpricing and shares required at least three years of historical return data. Using the methodology of Jegadeesh and Titman (1993), shares were sorted using the conventional 3, 6, 9 and 12 months cumulative return windows and assigned to one of 10 relative strength portfolios. Portfolio returns were calculated on an equally weighted overlapping basis with holding periods matching windows used for portfolio estimation. Momentum simulations were conducted in each market, resulting in 16 strategies per country. When considering the 16 simulations conducted in each country, 15 were significantly positive in the UK, 14 in Germany, 10 in China and none in Japan.

In order to determine the consistency of momentum profits across the markets considered, the sample was split into two equal sub periods. Momentum profits were found to be consistent across the sub samples for the UK and Germany. Interestingly, both China and Japans momentum profits were significantly weaker in the first sub-sample and improved drastically in the latter period. Following the methodology espoused by Conrad and Kaul (1998), momentum portfolios were resorted using weightings defined by each shares cross-sectional relative performance in excess of the market proxy. The effects of the technical variation were minimal for the UK and Germany, were 15 and 16 of the momentum portfolios achieved statistically significant returns over the sample period. The weighted relative strength momentum strategy did however affect the results of the momentum sorts conducted on the Chinese stock market as none of the momentum strategies achieved statistically significant positive returns. Like the equally weighted momentum strategy results, none of the Japanese momentum strategies yielded positive excess returns.

To identify whether other factors were driving momentum profits in the markets examined, risk adjusted returns were calculated using a country specific Fama-French three factor model. The results of the risk adjusted returns were virtually identical to the pure portfolio sorts as the UK, China and Germany achieved significantly positive alphas while Japans alphas were significantly negative. Importantly, momentum profits over the four economies examined could not be explained by market risk, size or value. In order to identify whether seasonality explained momentum profits, momentum profits were grouped based according to the month of their occurrence. Unlike Jegadeesh and Titman (1993) and Grundy and Martin (2001), momentum profits failed to show any form of seasonality, as January returns were not significantly different when compared to February to December. Lastly, following Rouwenhorst (1998), correlation analysis was conducted in order to determine whether momentum was a common component across the markets considered. The results of the correlation analysis indicated that although momentum profits were positive in three of the four markets examined, momentum did not seem to be a common component across countries as correlations were below generally below 15% (barring UK and Germany which achieved a correlation of 48%) and in some instances negative. The results of the study were consistent with the likes of Rouwenhorst (1998, 1999) as momentum profits in western economies were considerably higher than those in Asia.

Chui, Titman and Wei (2010) examined the extent of behavioral biases driving international momentum profits. The authors focused on two behavioral theories, namely overconfidence as described by Daniel, Hirshliefer and Subrahmanyam (1998) and underreaction to initial information per Barberis, Shleifer and Vishny (1998). In order to determine behavioral differences amongst countries, the study makes use of the 'individualism' index per Hofstede (2001). Hofstede (2001)[3] defined individualism to be "the degree to which people focus on their internal

[3] Hofstede is a world authority in behavioral psychology specializing in the study of "individualism"

attributes… to differentiate themselves from others". The authors consider share return data in 41 international markets over the sample period February 1980 to June 2003 and includes over the 20 000 individual shares. The authors further consider the Hofstede Index of each country as well as a number of other variables that may contribute to the behaviorally based variation in international momentum returns. In order to test the Hofstede Individualism index, the correlation between individualism, volatility and liquidity were examined as both the behavioral theories that describe momentum are generally accompanied with increased levels of volatility and liquidity.

In regression analysis, liquidity and volatility, proxied by turnover and monthly squared share returns respectively, were both significantly and positively related to country individualism, even after controlling for variables that have been used to explain volatility and liquidity. Consistent with other international studies of momentum, a six month estimation and holding period momentum strategy was applied across the 41 international stock markets on a share by share basis. Portfolios were sorted using a 30th / 60th percentile split in order to account for a potential relatively smaller sample size in a number of countries included in the study. Using the methodology of Jegadeesh and Titman (1993, 2001) allowance was made for a single month between estimation and investment in order to account for microstructure effects and overlapping portfolio returns, calculated on an equally weighted basis over the sample period. The results of the momentum sorts were consistent with evidence presented in previous international studies as the majority of countries exhibited statistically significant and positive excess momentum returns. 25 of the 41 countries exhibited positive and statistically significant momentum profits while Japan, Korea, Taiwan and Turkey achieved negative and insignificant excess returns.

In attempt to determine the effects of 'individualism' on momentum across country indices, countries were classified into one of three groups based on their individualism index using a 30th/60th percentile split. When sorting on both momentum and individualism, the results indicated that momentum profits increased monotonically with individualism, where the high individualism momentum returns exceeded the low individualism countries by 0.65% per month the average difference being significant at the 5% level. Moreover, excess returns of high individualism momentum portfolios over their low individualism counterparts were found in 14 of the 19 years of the sample period and translated into an annualized excess return of 8.57% per annum. The study then extended the analysis to consider longer holding periods, in order to identify whether reversal, as predicted by both behavioral models, was present in international momentum profits. Consistent with the behavioral explanations considered, reversals were consistently more extreme in high individualism countries, where high individualism countries reversals significantly underperformed low individualism countries by -0.3% per month. The findings of the study therefore favored behavioral explanations of momentum as the lack of consistency of momentum excess returns across geographies, coupled with greater momentum profits in countries with higher levels of individualism are unexplained by risk based pricing theories.

Herberger, Kohlert and Oehler (2011) studied the presence of momentum on the cross-section of Swiss stocks listed over the period December 1980 to February 2009. In order to determine the robustness of momentum profits, the study controlled for transaction costs, market risk and industry effects. The full data set was sourced from the Datastream database, where ADR's, Real Estate Investment Trusts and closed-ended funds were excluded resulting in a total sample of 469 shares over the sample period. Using the methodology of Jegadeesh and Titman (1993), shares were sorted based according to 16 momentum strategies, implying the application of portfolio estimation and holding periods of 3, 6 , 9 and 12 months. Consistent with Jegadeesh and Titman (1993, 2001) and Moskowitz and Grinblatt (1999), portfolios were allowed to overlap in order to increase the power of statistical tests.

Shares were accordingly sorted into one of ten decile portfolios where returns were calculated on an equally weighted basis. In order to mitigate micro-structure effects as well as short-term reversal, a single month gap was allowed between portfolio estimation and investment. In order to account for transaction costs, four proxies were used. The authors applied a generalized methodology based on the type of investor engaging in momentum strategies where three types of investors were considered, namely institutional, wealthy private client and private client. Each of the proxy investors was allocated an assumed transaction cost of 0.2%, 0.5% and 1% respectively. The fourth proxy relates to the proxy used by Grundy and Martin (2001), who found that the ceiling transaction cost on momentum portfolio was 0.375% for both the purchase and sale of the extreme portfolios. In order to adjust for market effects, the authors deducted the equally weighted market proxy of the shares considered from the excess momentum profits earned over the sample period attributable to the particular momentum strategy. In order to proxy for industry effects, the authors grouped the cross-section of shares based on one of four generalized sectors namely, technology, services, financials and production and calculated momentum profits of each.

Consistent with similar studies conducted on the cross-section of European exchanges, momentum profits for each of the 16 strategies considered were significantly positive and economically high. Notably, the best performing strategy was the 12 month /3 month estimation and holding period portfolio, achieving an excess average return of 1.5% per month on average. More importantly, a pattern emerged from the 16 strategies where excess return profits increased when estimation periods increased from 3 months to 12 months, while the opposite was found as momentum profits seemed to decline for a given increase in portfolio holding periods. The results of the gross returns were supported by the portfolio profits calculated in excess of the market as momentum returns maintained a positive relationship with portfolio estimation periods and a negative relationship with portfolio holding periods. In order to determine the effects of transaction costs on momentum profits, momentum simulations were run allowing for variation in the transaction costs proxies.

The results indicated that excess momentum returns were obliterated when using estimation periods of three and six months, but were significantly positive when estimation periods were greater than or equal to 9 months. To determine the effects of industry classification, intra-industry momentum portfolios were sorted using approach of Jegadeesh and Titman (1993, 2001). The findings did seem to indicate a form of industry effect, as there was significant variation in the intra industry momentum profits. The best industry momentum portfolio was that of technology, achieving a significant 1.82% per month, while the worst intra-industry momentum portfolio was the financial sector, achieving a statistically insignificant 0.09% per month. The results favored the findings of Grundy and Martin (2001), as momentum of the Swiss stock exchange was significantly profitable over the sample period but was largely explained by significant momentum in the technology industry.

Aharoni, Ho and Zeng (2012) attempted to identify whether momentum profits achieved on the cross-section of Australian shares conform to the hypothesis of Sagi and Seasholes (2007). The study considered shares listed on the Australian Stock Exchange over the period January 1993 to December 2006. Sagi and Seasholes (2007) hypothesized that momentum profits were directly related to the level of growth options, where a larger portfolio of growth options resulted in positive autocorrelation in share returns, resulting in momentum profits. Further, the level of growth options dictates the level of risk, implying that momentum profits are in fact compensation for investing in high growth option shares. In order to test the hypothesis, shares were sorted on historical cumulative returns as well as other proxies of growth options such as revenue growth, book-to-market ratio and market conditions. Following the methodology of Jegadeesh and Titman, overlapping momentum portfolios were estimated monthly where shares were sorted based on their historical cumulative return over the previous 3, 6, 9 and 12 months and held for identical window periods and excess portfolio returns were calculated on an equally weighted basis. The results of the pure momentum strategy produced excess returns that were the highest in the medium estimation and holding (six month) period, yielding a significant 1.5% per month on average over the sample period. The results were consistent with the findings of Demir *et al.* (2004), yet in order to further test the presence of momentum, portfolio simulations were re-run and value-weighted portfolio returns were estimated. Consistent with international evidence, value-weighted momentum excess returns were economically smaller, yet were still significant and amounted to 0.98% per month on average (specifically for the 6 and 9 month estimation and holding period portfolios). The major determinant of the lower value weighted performance was due to value-weighted loser portfolios achieving significantly higher returns than equally weighted losers on average.

In order to test the hypothesis of Sagi and Seasholes (2007), three dual sorting methodologies were implemented where momentum was combined with revenue volatility, book-to-market and market conditions. Earnings volatility was considered a proxy for growth options, as option values

tend to have a positive relationship with the volatility in the underlying asset. Portfolios were sorted jointly on historical cumulative return and earnings volatility assuming both equally and value weighted returns. The findings indicated that momentum profits were significantly positive in high earnings volatility firm with the six-month estimation and holding period high volatility momentum portfolio achieving 2.2% per month and was significant at the 1% level. In contrast to the high volatility momentum portfolios, the momentum profits of the low volatility firms were barely positive and not significant at any estimation or holding period.

The result was that high volatility momentum portfolios outperformed their low counterparts by 1.5% per month. Sagi and Seasholes (2007) used the book-to-market ratio as a proxy for growth options (where a negative relationship is expected between growth option and the book to market ratio) and the same sorting mechanism was applied on the cross-section of Australian shares. The results of the dual sort on book to market and momentum were consistent with the findings of Sagi and Seasholes (2007) as low book-to-market momentum portfolios achieved excess returns of 2.6% per month on average while high book-to-market momentum shares achieved average monthly returns of 1.3% per month on average. Lastly, excess returns of low over high book-to-market momentum shares equated to approximately 1% per month, irrespective of estimation and holding period. The authors further found that the profitability differential was largely attributable to loser shares as high book-to-market losers achieved consistently higher returns (1.7% per month on average) than the low book-to-market losers (0.7% per month on average).

The third and final enhanced momentum strategy examined momentum profits based on general market conditions. The authors defined market conditions based on the markets returns over the previous 12 months. The purpose of the market condition momentum relates to the assertion by Sagi and Seasholes (2007), that high growth option firms achieve higher returns in bull markets. Consistent with the findings of Sagi and Seasholes (2007), momentum returns over the sample period tended to be higher in positive market states, but the return differential between momentum strategies in bull and bear markets was not statistically or economically different from zero, differing to the predictions of the growth options hypothesis. The authors attributed their findings to the limited sample period as therefore the limited measure of determining market states. The findings of the study therefore indicated that a risk based explanation of momentum on the cross-section of Australian shares is plausible as two of the three dual portfolio sorts indicated that momentum profits were linked to proxies of high growth options and consistent with a risk based framework of asset pricing.

Muller and Ward (2010) considered 70 country indices that form the basis of the MSCI world index over the period 1970 to 2009 and tested whether momentum and long-term reversal explains the cross-sectional variation in returns. For each of the country indices represented on the MSCI,

time-series data was collated using market proxies that contained return data on mainly primary listed companies, thereby reflecting highly liquid and tradable representations of each country index. All returns were market capitalization weighted and dollar denominated. The study considered both momentum and long-term reversal similar to the methodologies of Jegadeesh and Titman (1993) and De Bondt and Thaler (1985, 1987). Each country index was treated as if it was a single share and ranked according to its estimation period historical return and grouped based on historical return into winner and loser country indices. Winner indices were then fictitiously combined into equally weighted portfolios and held for a holding period window. An identically opposite portfolio simulation approach was used for the long-term reversal where historical losers were fictitiously invested in over various investment horizons.

All of the strategies applied were compared to an equally weighted index based on the universe of equity indices that formed the MSCI world index. Importantly, the authors emphasized the fact that the market proxy used as a comparator conformed to the portfolio weighting system used by both the momentum and long-term reversal strategies. The methodology applied removed the effects of start-date and timing effects biases that generally effect time-series portfolio optimization studies. The authors considered three different sub-samples, allowing for the variation in sample sizes throughout the entire sample period. When considering the entire sample through time, the authors found that using specific estimation and holding periods, both the winner and loser strategies outperformed the equally weighted market proxy. The best performing loser portfolio used an estimation period of 44 months and a holding period of 36 months, achieving and annualized return of 19% per annum, outperforming the 14.5% achieved by the equally weighted benchmark.

Similarly, the authors found significant momentum effects, with the best performing momentum strategy applying an estimation period of between 6 and 9 months and a holding period of 1 month. The top performing momentum strategy achieved returns of 26% per annum, which was almost double the equally weighted benchmark of 13.9%, earning an annualized outperformance of 10.6% over the sample period. Most notably, the authors found that the core difference between the momentum and long-term reversal strategies were their strength of presence through time. The long-term reversal strategy only showed significant outperformance in the beginning of the sample period, but diminished through time. Momentum however, was found to be both persistent and present throughout the sample period and relatively short lived, with the main portion of momentum profits being earned over the first month of investment.

Fama and French (2012) examined size, value and momentum in international stock returns in order to identify whether the factor styles are present and significant and differed to prior literature by incorporating smaller capitalization shares. A secondary aspect of the study considered whether the Fama and French (1993) three factor model and Carhart (1997) four factor model

are able to explain the variation in international shares sorted independently on size, value and momentum. The sample period of the study spanned from November 1989 to March 2011 and included data on all stocks of 23 countries. All returns were calculated on a dollar basis where excess returns were defined in excess of the US monthly T-bill. In order to ensure a large amount of shares in each portfolio, the 23 countries were combined into four regions, namely North America, Japan, Asia Pacific and Europe. Global portfolios were also estimated where the entire combined cross-section was used. Shares were sorted on each factor using a 2 x 3 sort were the core factor took the form of the two extreme portfolios implying small less big, value less growth and winner minus loser. Momentum portfolios were constructed per the methodology of Jegadeesh and Titman (1993) as shares were sorted on their historical 11 month cumulative return, thereby excluding the last month of the 12 month window in order to account for bid-ask bounce and microstructure effects.

The initial findings indicated that equity risk premia over the sample period varied amongst the regions as value weighted market returns were positive and significant in three of the four regions (Japan was an exception) while the global equity market risk premium over the full sample equated to 0.44% per month. Notably, the value premium was significantly positive in all regions, ranging from 0.33% for North America to 0.62% for Asia pacific and seemed to maintain a negative relationship with size, yet for all regions considered, there was no apparent size premium. Like most momentum studies, the authors found that momentum was globally present, barring Japan. The global excess momentum return of winners over losers was 0.62% per month and was significant at the 5% level. Like the value effect, momentum profits seemed to maintain a negative relationship with size, where on average excess momentum profits on small shares amounted to 0.82% per month while large shares only achieved 0.41% per month.

A central aspect of the study was to determent whether a three or four factor model is able to explain dual sorted portfolios on a global, regional and inter-market scale. In order to test the various models, shares were sorted on size and momentum into one of 25 portfolios using variations of the sample of shares, the first being the entire universe of shares considered (global) then regional sorts. Each model was tested using the Gibbons, Ross and Shanken (1989) F-test on time series alphas, absolute average alpha, the standard error of alpha and R^2. On a global basis, the four factor model failed to explain the cross-sectional variation in portfolio returns when using global risk factors. The average intercept was 0.14% per month, while the GRS statistics rejected the null of all intercepts being jointly zero at the 1% level. A major source of lack of performance was potentially attributable to the inclusion of micro-cap shares in portfolio sorts. A second set of time-series regressions were run excluding micro-caps thereby limiting the test portfolios to 20. The results were more in favour of a global four factor model that included momentum as the average alpha dropped to 0.09% per month, yet the global four factor model was still inadequate as the GRS statistic rejected the null at a 5% level. Importantly, when applying

the global four factor model to the regional portfolio sort, in 3 of the 4 regions the GRS statistic rejects the null at a 5% and the exclusion of microcap does not add explanatory power.

Considering regional portfolios and the use of regional factors, micro-caps do seem to be a major impediment to the effectiveness of regional four factor models. Considering North America, the inclusion of the micro-caps results in the GRS statistic rejecting the four factor model, yet when excluding the micro-cap shares, the GRS statistic fails to reject the four factor model and average alphas decrease to 0.08% per month. The results indicated that a four factor model was appropriate on the cross-section of shares in the North America region. The results of regional Asia-Pacific and Europe size-momentum portfolios and regional risk factors were less convincing. Irrespective of the inclusion or exclusion of micro-cap shares, the GRS statistics reject four factor regional models, as time-series alphas were significant and economically high with the Europe momentum-size portfolios achieving 0.18% and 0.14% per month, including and excluding micro caps. The Asia Pacific results were even less impressive as average alphas were 0.27% and 0.19% per month when including and excluding micro-caps while in both scenarios the GRS statistic rejected the four factor models at the 1% level. The authors concluded that a major determinant of model efficiency is based on the tilt of the underlying portfolio, where if portfolio exposures are largely in the extreme ranges of size and momentum, regional portfolios fail to explain cross-sectional variation. Further, the authors found limited evidence in favor of global risk models, finding regional models fared better when considering average time-series alphas and GRS test statistics.

Asness, Moskowitz and Pedersen (2013) conducted a comprehensive study across various exchanges and asset classes asserting that there are two core factors that drive returns, namely value and momentum. The study considered four global equity markets for the purposes of single share momentum namely the US, UK, continental Europe and Japan using sample periods of January 1972 to July 2011 for the US and UK and January 1974 to July 2011 for Continental Europe and Japan. A number of restrictions were applied where at each sorting period shares were ranked based on their market capitalization in descending order and qualified for inclusion if they formed part of the cumulative 90% based on market capitalization. The result of the criteria was that all shares considered were highly liquid and tradeable set of securities. The study also included country equity index futures of 18 developed markets over the period January 1978 to July 2011, currencies of 10 developed countries over the period January 1979 to July 2011, government bonds for 10 developed countries over the period January 1982 to July 2011 and lastly commodity futures based on 27 soft and hard commodities over the period January 1972 to July 2011.

The breadth of the study is unique to the literature and the author's utilized conventional methods of defining momentum and value in all the asset classes considered. For equities the authors

used the book-to-market ratio to proxy value while momentum was defined using the methodology of Jegadeesh and Titman (1993) using a 12 month estimation period and allowing for a single month between estimation and investment in order to remove possible microstructure effects and short-term reversal in share returns. The momentum measure was standardized across all asset classes yet in order to define value, the authors used inverse of five year cumulative return for assets that did not have book values such as currencies, commodities and bonds. The time-series value measures were inspired by De Bondt and Thaler (1985) and Fama and French (1996) as both showed that long-term reversal proxies such as the inverse of five year return generate portfolios that were highly correlated with book-to-market sorted portfolios. Applying the measures of value and momentum described, momentum and value portfolios were constructed in each asset class using 30th /40th /30th percentile split (high, medium and low) resulting in 48 portfolios. Notably, equity returns were value weighted while all other asset returns were equally weighted. For each asset sort, excess momentum and value premia were constructed using a modified methodology of weighting, were assets/securities were weighted based on their cross-sectional rank less the cross-sectional average rank of the signal (high, medium or low momentum or value). The result is that the cumulative weights of all assets sum to zero, resulting in a natural long-short position required for excess return premia.

The results of the value and momentum sorts were consistent with international literature. In terms of value, every equity market considered produced a significant value premium, with the strongest performance from Japan. Similarly, all markets produce a significant and positive momentum premium, barring Japan (which was positive but not significant). Importantly, throughout all the indices covered, the value and momentum premia were significantly negatively correlated, averaging -60%. The authors further noted that when combining value and momentum, irrespective of index, the profits of the dual strategy outperformed the univariate strategies and this was most notable for Japan. Even though Japan did not produce any obvious momentum premium, the combination of momentum and value achieved a significantly higher Sharpe ratio (0.88) when compared to value alone (0.79). In order to test whether the intra-market structures were visible across indices, global value and momentum portfolios were created by combining portfolios using averaging as well as weighting each market by the inverse of their ex-post sample standard deviation (the method results in separate assets contributing approximately equal amounts to portfolio ex post volatility). The authors found that using both methods arrived at similar Sharpe ratios for global momentum and value portfolios, indicating strong correlation structures of for global value and momentum.

The results of the equity sorts extended to the other assets considered. Even though there was significant variation in both momentum and value returns in each of the asset classes over the sample period, value and momentum, irrespective of asset class maintained a significantly negative correlation. Using the same methodology applied to equities, combination portfolios

were created by weighting assets based on the inverse of the ex-ante standard deviation. The result of the combined weighting schematic was that all portfolios, irrespective of asset class maintained similar (if not better Sharpe ratios) implying that momentum and value premia were consistent within the asset classes considered. In order to determine the comovement of value and momentum across the diverse asset groups, the universe of assets was first stratified into equity and non-equity assets. The results of the correlations between the average return series provided further evidence in favor of global momentum and value factors. Global non-share momentum was significantly and positively correlated with global share momentum, achieving a correlation coefficient of 37%, while global non-share value achieved a significantly negative 16% correlation with global share momentum.

The authors further considered the correlation between global value and momentum within each of the global asset groups. The results were similar as global value (and momentum) were significantly and positively correlated to the all the non-stock value (momentum) asset portfolios while the inverse held when compared to the non-stock momentum (value) asset portfolios. The results of the study were two fold. Firstly, the findings indicated that irrespective of asset class, both value and momentum are present and importantly, negatively correlated. Secondly (and critically), unlike Fama and French (2012), the study found evidence of momentum and value being globally priced, providing proof in favor of a risk based explanation behind the presence of momentum that extends beyond behavioral explanations and equity based risk explanations such as growth options and other equity risks.

2.2.3 South African evidence of momentum in share prices

Documented evidence of momentum on the cross-section of shares listed on the JSE is limited when compared to international literature on the subject. Most, if not all of South African finance literature is related to anomalies that have been originally discovered and discussed in international literature and tested on foreign shares and exchanges. Therefore, most of the evidence discussed pertains to tests conducted on the JSE but can be directly linked to international literature and findings. Fraser and Page (2000) considered the hypothesis of Asness (1997) relating both to the identification of momentum and value on the cross-section of Industrial shares listed on the JSE as well as determine the interaction between the styles. The study considered share return data on the cross-section of industrial shares listed in the JSE over the period January 1973 to October 1997. In order to proxy for momentum, the authors used the arithmetic average over the previous 12 months, applying a notably different methodology when compared to international literature, specifically not using cumulative returns or skipping a single month in order to mitigate the effects of bid-ask bounce and micro-structure issues.

Two proxies were used for value, specifically dividend yield, calculated as the previous year's cumulative dividends scaled by the market price as well as the book-to-market ratio, which was adjusted in order to mitigate the effects of look-ahead bias. Portfolios were then formed monthly, where value portfolios were formed using a relative ranking system based on the sector relative dividend yield and natural logarithm of book-to-market. The momentum strategy did not consider the sector relative momentum but rather the entire cross-section of industrial shares. Portfolios were sorted into quintiles on an equally weighted basis and reweighted monthly. Further, the authors also sorted shares based on size and market beta. In univariate tests, the authors found that value, proxied by both dividend yield and the book-to-market ratio, has predictive power in terms of industrial shares listed on the JSE as in both cases monthly average returns increased monotonically when moving from glamour (low dividend yield and book-to-market ratio) portfolios to the value portfolios. For both strategies, value shares outperformed growth shares by approximately 0.6% per month and the difference was significant at the 1% level.

Consistent with international literature, when sorting on historical average returns, historical winners outperformed historical losers. Historical loser shares achieved average monthly returns of -1.89% while average winner shares produced monthly average returns of 0.39% per month. The difference between the extreme portfolios was approximately 0.76% per month and was significant at the 1% level. In order to determine the interaction between value and momentum, bivariate tests were conducted where 25 portfolios were formed using the natural logarithm of the book-to-market ratio and the average historical 12 month of returns. Unlike the assertion of Asness (1997), value and momentum seemed to be highly independent in bivariate tests. Momentum seemed to maintain a minimal interaction with value, as momentum was both persistent and strong in both long-only and excess returns, achieving significantly positive returns, irrespective of the value strata. The authors found similar conclusions when allowing for variation in the book-to-market ratio and holding momentum constant. The findings therefore negated the assertion of Asness (1997) as not only did value and momentum singularly have predictive power on the cross-section of industrial shares on the JSE, but did not seem to hold any significant inter-relationship as both were significant and present even in bivariate sorts.

Van Rensburg (2001) conducted an in-depth study that examined a number of internationally researched stylistic factors applied on the cross-section of industrial shares listed on the JSE. The core purpose of the study was to determine whether the style factors explained expected returns in industrial shares listed on the JSE over the period February 1983 to March 1999. Consistent with international studies of this nature, accounting variables were lagged 3 months in order to prevent look ahead bias while a liquidity filter was applied where shares were excluded if they achieved median volumes in and below the bottom 5th percentile at each portfolio formation date. The styles considered were classified into one of three groups namely, "value", "future earnings growth" and "investor rationality". Portfolio sorts were conducted on a monthly basis

where shares were ranked on each of the styles considered and sorted into one of three portfolios. Portfolio returns were calculated on an equal and value weighted basis and the fictitious zero cost excess return time-series was estimated. It should be noted that momentum portfolios were sorted in two distinct ways, namely only considering the positive historical average return shares or considering the entire cross-section of shares at portfolio sort. The former resulted in a concentrated portfolio that isolated the best historical performers and obviously limited the number of shares in each portfolio.

The results of the raw returns indicated that momentum (in various forms) was significant and present on the cross-section of shares analyzed during the period. For example, the momentum strategy that applied a historical 12 month estimation period and limited the cross-section to historically positive average return shares achieved an excess return of 1.52% per month on average and was significant at the 5% level. The next best momentum proxy was the 12 month momentum style that considered the entire cross-section of shares, achieving a positive excess return of 1.07% per month and was significant at the 5% level. Notably, both the positive historical average only and entire cross-section six month momentum strategy achieved significantly positive excess returns (at the 5% and 10% level) in excess of 0.85% per month. Consistent with international literature, momentum excess returns that utilized a single month as the estimation period achieved significantly negative returns providing evidence in favor of short-term reversal in share returns. The study then evaluated the risk-adjusted performance of each of the styles considered using time-series regressions. Both a conventional market and an augmented market model that used both the FINDI and RESI as market proxies was applied to determine risk-adjusted excess returns in the form of time-series alphas over the sample period. Of the top ten styles, four were momentum styles that utilized 12, 6 and 3 month estimation periods and limited the cross-section to positive historical return shares. The top performing style was the 12 month estimation period momentum portfolio and achieved highly significant time-series alphas of 1.54% and 1.52% using the CAPM and APT (augmented market) models respectively. Notably, the usage of the extended APT like market model enhanced momentum returns, where alphas were actually as high, and in some cases higher, than the pure CAPM market model. The study confirmed the findings of Fraser and Page (2000) indicating that momentum was both present and a significant factor on the cross-section of industrial shares listed on the JSE.

Van Rensburg and Robertson (2003) continued on the same line of research pursued in van Rensburg (2001) where style based variables were regressed on share returns in order to determine their explanatory power in terms of the cross-section of shares listed on the JSE. The sample period spanned from July 1990 to June 2000. Like van Rensburg (2001) a cross-sectional liquidity filter was applied where shares were excluded if their monthly turnover ratio was below 1% per month. The study considered 24 various styles that were grouped based on value, future earnings growth, bankruptcy or financial distress, irrationality and neglect. Momentum variable

were classified under the irrationality group and included 1, 6 and 12 month estimation period momentum proxies. The holding period was assumed to be one month for every variable in the study, therefore the momentum variables effectively represented three variations of estimation and only a single category of holding period.

For each of the 24 styles considered, a single factor share-by-share cross-sectional regression was run reminiscent of a Fama-Macbeth cross-sectional regression for each style where the dependent variable was the realized risk-adjusted return for each share and the independent variable was the lagged style. Notably, all of the stylistic variables were standardized to have a mean of zero and standard deviation of one, allowing for the comparison of coefficients in terms of similar magnitudes. Two methods of risk-adjustment were used where time-series alphas were estimated first using the pure market model (CAPM) as well as an APT style model per van Rensburg (2002), which used the FINDI and RESI indices. The process was repeated using a form of step-wise regression where styles were added in order to determine the joint significance of all the 24 factors considered in the study. In univariate tests, using three differing measures of expected returns (raw and risk adjusted), six variables were consistently significant and included price to NAV, size, price-to-earnings ratio and cash flow-to-price. Most notably, the study found that none of the momentum variables considered were significant predictors of one month expected returns while both size and value were.

Venter (2009) tested for intraday momentum and reversal on specific shares listed on the JSE over the 2007 trading year. The Intraday momentum trading strategies considered were conceptually similar to the momentum of Jegadeesh and Titman (1993), but relied on higher frequency trading periods over significantly shorter periods. Since the study considered high frequency and short horizon estimation and holding periods, the sample period was limited to 2007, where shares were excluded based on a market capitalization floor value of R1bn and required share data in the form of mid-quote prices. The usage of mid-quote prices was in order to mitigate possible bid-ask bounce and is equivalent to skipping a month between portfolio estimation and investment in medium term momentum studies. In order to remove the effects of the opening and closing auction bias, where the best ask prices were possibly below the best bid, prices were only considered after 9:15 and before 16.45. Using a methodology reminiscent of Jegadeesh and Titman (1993), shares were sorted based on their recent returns, where estimation periods took the form 0.5 to 2.5 hours, allowing for 0.5 hour increments. Holding periods were considerably longer and were varied between 1-5 hours.

The results of the various portfolio simulations found that the average returns of all the portfolios, irrespective of whether they were winner or losers over the estimation periods, were not significantly different from zero. Furthermore, the extremity of the returns and standard deviations of the strategies seemed to be confined to the lower size decile of the sample considered.

Interestingly, the results portrayed a greater deal of support in favor of contrarian strategies in intraday trading as loser portfolios, irrespective of formation period, achieved positive returns while the extreme winners were consistently more negative. Notably, the result was exacerbated when considering small capitalization shares as reversal was far more pronounced in the lower market capitalization decile. In robustness tests, a series of bid-ask spread filters were applied where shares were excluded assuming 10, 20 and 30 basis point bid-ask spread thresholds. The results indicated that contrarian profits responded negatively to the increased bid-ask spread filter. The author concluded that the Jegadeesh and Titman (1993) ranking style was not an appropriate means for determining the optimal strategy in intraday trading as no clear result was garnered regarding the optimal strategy based on estimation and investment periods.

Hoffman (2012) investigated the presence of stock market anomalies on the cross-section of shares listed on the JSE over the period 1985 to 2010. The explanatory variables used included size (market capitalization), value (book-to-market ratio), historical price momentum measured over the previous 12 months, net shares in issue, accrual in operational assets and growth in total assets. Initially, both time-series and cross sectional correlations were run using two proxies of expected returns, namely one month and one year future returns. In order to determine the consistency of the correlation values, the average standard deviations for each correlation coefficient were also presented. Consistent with international and local literature, size, value and momentum maintained correlation coefficients that were negative for size and positive for value and momentum. In cross-sectional regression tests, the study mimicked the methodology applied by Fama and French (2008) where share by share time-series regressions were run monthly starting from April 1988 to December 2010 where the dependent variable took the form of the 12 month future return. Regressions were re-run using different stratum of the full sample based on market capitalization. The monthly coefficients were then used to report the average coefficient, standard deviation and t-statistics. The regression results were then compared to the results of Fama and French (1998) in order to determine the comparative style effects on the JSE to the NYSE. Consistent with international results, both size and value maintained significantly negative and positive average coefficients over the sample period. Similarly, positive regression results were found for the 12 month price momentum variable, which was both positive and significant across all size groups. The average coefficient was for all shares within the sample was 0.152% and was significant at the 5% level.

The magnitude of the momentum coefficient seemed to be sensitive to the size of the underlying population as the largest stratum produced the lowest momentum coefficient of 0.107% and was significant at the 10% level, while the smallest tertile of shares produced the highest momentum coefficient of 0.209%, almost double that of the largest tertile and was significant at the 1% level. Since size and value were both highly significant and well documented, both internationally and locally, regressions were rerun excluding size and value as independent variables. The results

once again proved that over the sample period, momentum in share prices was a significant predictor of expected returns. Considering all shares listed, historical momentum produced an average coefficient of 0.151% and was significant at the 1% level. Interestingly, the micro stratum actually produced the lowest momentum coefficient while the medium stratum achieved an average coefficient of 0.4% per month and was significant at the 1% level. Lastly, portfolio sorts were conducted, following the methodology of Fama and French (2008). Portfolios were sorted on the styles considered in both the correlation and cross-sectional regression analyses. Notably, even though momentum maintained a positive correlation with future returns and cross-sectional average momentum coefficients were significantly positive and constant throughout the sample period, portfolio sorts provided the weakest evidence in favor of momentum being a significant explanatory variable for expected share returns. For each style considered, both value and equally weighted returns were calculated while portfolio sorts were applied to the full sample of shares as well as sub-samples based on size.

Considering the entire sample of shares, the equally weighted average excess momentum return over the sample period was an insignificant -0.6% per month. However, the value weighted average excess return was 2.5% per month and was significant at the 1% level. The poor performance of equally weighted momentum was attributable to the negative excess return achieved by the microcap shares which equated to -0.1% per month and was significant at the 5% level. The performance in the small and big stratum was far more positive with both achieving positive excess irrespective of the weighting mechanism. The core finding of the study was that the cross-section of shares conforms to evidence found on the US cross-section of shares as the key variables that seem to drive expected share returns on the JSE are size, value and momentum, consistent with the model predicated by Carhart (1997).

Hodnett, Hsieh and van Rensburg (2012) conducted an in-depth study into firm specific characteristics used as investment styles on the cross-section of shares listed on the JSE over the period January 1997 to December 2007. The authors considered 5 categories of styles, namely: fundamental ratios, solvency, growth, size and momentum and analysts forecasts. The authors only considered firms that were listed at 31 March 2009, implying that the study was prone to survivorship bias, yet the authors argued that the set of shares considered were highly liquid and thereby represented an investable universe of shares. Moreover, the authors applied a liquidity filter that excluded shares with turnover ratios less than 0.01% in the particular month that it occurred. The data was further winsorised at the 99% level where all attribute values were assigned the 99.5^{th} and 0.5^{th} percentile as maximum and minimum values. Style attributes were then de-meaned implying that each share attribute was subtracted from the cross-sectional average each month in order to add ease of interpretation to the cross-sectional regression coefficients.

Like van Rensburg (2001), the study used the one-month lead returns for each attribute. All of the lagged attributes were then cross-sectionally regressed against the lead return for each share considered in the cross-section and the time-series cross-sectionally estimated betas were then averaged using non-parametric t-tests in order to estimate the average factor payoff for each of the 5 categories outlined above. Regarding momentum, the study specifically considered six momentum variants, all of which conformed to the methodology of Jegadeesh and Titman (1993). The considered variations of momentum estimation periods included 1, 3, 6, 12 and 12 less 1 month estimation window periods. The authors found that one month prior momentum produces a negative coefficient over the entire sample period as well as the two sub periods. The best performing momentum proxy was the 12 less 1 month momentum factor followed by the 12 month momentum factor. The results were consistent with the findings of Jegadeesh and Titman (1993, 2001) as well as van Rensburg (2001) as share returns seemed to display a short-term reversal while longer estimation periods seemed to produce higher momentum profits. More importantly, the results indicated that the skipping of one month in order to avoid micro-structure effects resulted in an increased momentum profit of 20 basis points per month on average, implying that micro-structure effects do seem to negatively affect momentum profits on the cross-section of shares listed on the JSE.

Muller and Ward (2013) conducted an in-depth study into the numerous styles considered internationally as well as on the cross-section of shares listed on the JSE. The study considered a sample period from January 1985 to December 2011 but only included the top 160 shares based on cross-sectional market capitalization through time. The authors argued that the benefit of the limited universe is that the sample represented approximately 99% of the total market capitalization of the JSE as well as being a highly tradeable liquid proxy. The data was free of survivorship bias as delisted shares were included in the overall analysis, returns were adjusted for various corporate actions including unbundling's, consolidations, share splits and dividends while all accounting ratios were calculated to account for look-ahead bias assuming a three month lag. The methodology applied was consistent through all the styles analyzed where portfolios were sorted on an equally weighted basis using the entire universe of shares into one of five portfolios based on the style considered where portfolios were updated quarterly. The authors further argued that arithmetic averaging contains bias and opted for cumulative returns plotted in a time-series fashion.

The styles considered were grouped into three categories that were summarized as financial ratio based styles, which related to accounting based measures, market based styles and behavioral based styles. The behavioral based styles were confined to momentum in share prices using an estimation period of 12 months and holding period of a single quarter. In order to further strengthen the results, the authors applied a methodology akin to a forward step-wise regression, combining styles that contributed the most to overall style performance. In momentum sorts,

variations of estimation periods were used varying from 1 to 18 months. The optimal estimation period was found to be 12 months, however, the authors solely considered a holding period of 3 months, not allowing for the testing of an optimal portfolio holding period. Further, the study did not allow for a gap between portfolio estimation and holding, as espoused by both local and international literature, in order to account for bid-ask bounce and microstructure effects. Irrespective, it was found that momentum was the best performing style, achieving a premium of 18.6% per annum on average over its loser counterpart over the sample period. Furthermore, the authors found that the momentum style was the best combination style portfolio; producing the best overall results when combined in bivariate sorts with return on capital, cash flow to price and earnings yield. Of the three combination styles, both cash flow-to-price and earnings yield are considered value proxies, therefore the findings were consistent with those of Asness *et al.* (2012), regarding the cross-sectional persistence of value and momentum in and across asset classes.

Page, Britten and Auret (2013) considered the interaction between liquidity and momentum on the cross-section of shares listed on the JSE over the period January 1995 to December 2010. The study was free from survivorship bias, as delisted shares were not dropped from the sample, monthly returns were adjusted for all significant corporate actions such as dividends, unbundling's, consolidations and share splits. In order to be eligible for sorting purposes, a share required at least 12 months of historical return data, volume data and number of shares in issue. In univariate momentum sorts, shares were classified into one of five portfolios based on historical cumulative returns measured over varying estimation periods. The estimation windows used were identical to those used by Jegadeesh and Titman (1993, 2001), namely 3, 6, 9 and 12 months. The results of the univariate sorts indicating that at all momentum portfolios, irrespective of estimation or holding period, experienced significantly positive excess returns. Notably, momentum excess returns seemed to increase as portfolio estimation periods increased and reached a pinnacle at 9 months. Further, portfolio returns seemed to be highest using a holding period between 6 and 9 months. The best performing simulation was the 6 month estimation; 9 month holding period momentum portfolio, which achieved excess returns of 2.12% per month on average.

In order to consider the persistence of momentum, simulations were re-run on two sub-samples over the periods January 1995 to December 2002 and January 2002 to December 2010. The authors found that momentum profits were significantly higher over the first sub-sample as the maximum excess return achieved was 2.6% per month, while the maximum momentum return in the second subsample was 1.77% per month. On average, excess momentum returns in the latter sample were between 0.36% lower per month and the difference was significant at the 10% level.

Bivariate sorts were conducted where shares were sorted independently on cumulative historical returns and average turnover over the previous 12 months. The results were 48 portfolios sorted on four estimation periods, four holding periods and three stratum of liquidity. The results of the bivariate sort indicated that momentum excess returns maintained a positive relationship with liquidity. In the highest liquidity stratum, momentum excess returns were positive and significant in 14 out of 16 simulations, with the best performing sort being the 6 month, 9 month estimation and holding period, achieving excess average profits of 3.13% per month. Notably, when moving from the high to low liquidity stratum, momentum excess returns decreased monotonically, irrespective of estimation and holding period. The authors included a number of caveats with respect to their findings, specifically that arithmetic portfolio returns were used as opposed to buy-and-hold geometrically compounded returns. Furthermore, the authors conceded that the usage of a single liquidity proxy may be inappropriate, specifically due to the limited evidence pertaining to the choice of liquidity proxies on the JSE.

2.3 WHAT DRIVES MOMENTUM IN SHARE PRICES?

The previous section considered the plethora of evidence regarding the global (and local) phenomenon of momentum in share prices. The fact that momentum is found globally across various equity markets favors the notion of a universal momentum factor that partially (and jointly) drives shares returns, thereby contributing to the cross-sectional variation in share prices. Such an argument is consistent with a ‘risk’ based explanation of momentum in share prices, implying that the additional return that winner shares achieve over their losers counterparts is compensation for a systematic risk.

A converse stream of literature has emerged that favors a systematic mispricing in share returns, implying that momentum in share prices is actually driven by systematic behavioral biases that are present across markets. Notably, the study of momentum (as well as long-term reversal) in share prices is in some part responsible for the new string of financial theory that rejects risk based explanations in favor of market based psychological drivers of stylistic factors or mispricing (hereafter “behavioral finance”). It should be further noted that the broad categories of ‘risk’ and ‘behavioural finance’ are not the exclusive hypotheses applied in literature to explain momentum in asset prices. Osler (2000) describes a model that considers market micro-structures and flow of orders which contribute to autocorrelation in share prices leading to momentum and long-term reversal. Silber (2004) and Garleanu and Pedersen (2007) attribute momentum and long-term reversal to central banks and financial institutions where risk management practices and the slow diffusion of market information can drive increased auto-correlation in asset prices.

In lieu of the purpose of this study and the key research questions presented, specifically determining whether momentum is a dominant factor that explains the cross-sectional variation

in share returns on the JSE, the most plausible and generally accepted explanations are risk or behavioural biases. The sections that follow will investigate the literature and evidence supporting both risk and behavioral explanations of momentum.

2.3.1 Behavioral explanations of momentum

Lakonishok, Shleifer and Vishny (1994) attempted to develop a behavioral theory that explains the value phenomenon. The authors acknowledged that many studies had considered the existence of the value premium in share returns yet, there were mixed explanations behind the drivers of the value. The study considered the two emergent schools of thought, where the first and more theoretically appealing (and consistent) reasoning was inherent risk of the strategy in question, while the other less popular and more nouveau approach, attributed the success of value shares through time to contrarian investment and extrapolation, therefore the inherent psychology of investors. Covering the sample period April 1963 to April 1990, shares listed on the NYSE were sorted on a number of value proxies namely book-to-market, earnings yield, cash flow-to-price and sales growth. In each of the simulations conducted, the highest value proxy portfolio outperformed its glamour counterpart. The authors attributed the excess returns not to 'risk' but to behavioral hypotheses developed by Kahneman and Tversky (1982), where individual's overweight information contained in past data and fail to correctly weight historical data in terms of forming realistic expectations.

In order to test the hypothesis of Kahneman and Tversky (1982), dual sorts were conducted using sales growth in combination of other metrics of value. The authors found that bivariate sorts almost always outperformed univariate sorts, implying that when using two forms of value (current and expected), the value phenomenon was more pronounced. The finding was consistent with the assertions of Kahneman and Tversky (1982) as ratio proxies of value were considered indicative of historical data while sales growth was considered an expectation regarding earnings performance. The fact that combined strategies that invested in high value ratio and low sales growth shares achieved the highest returns was consistent with investors overweighting historical information and over-extrapolating the historical information into current and future expectations. This initial study, even though applied to the value phenomenon, initiated the divergent thinking that led to the inception of behavioral finance and the psychological explanations behind momentum over the medium term in share prices.

Chan, Jegadeesh and Lakonishok (1996) attempted to relate momentum in share prices to 'underreaction' by the market to new information, specifically in the form of earnings surprises. A core issue considered is whether momentum is driven by risk or behavioral biases in the market. Unlike size, value and long-term reversal, all of which have been rationalized from a risk perspective, momentum fails to attract any form of risk based explanations. A core assumption of

the study was the linking of momentum in share prices to revisions in earnings and specifically underreaction to news regarding earnings. The study considered three hypotheses. The first conjectured that if share price momentum is directly linked to earnings momentum, after controlling for earnings momentum price momentum would be reduced to not being significantly different from zero. A possible secondary explanation of momentum was that of overreaction to information resulting in positive feedback, where market participants overweight current information, resulting in momentum that will subsequently reverse. The final hypothesis was that both momentum strategies exploited underreaction to differing aspects of information implying that earnings momentum would not subsume price momentum and *vica versa*.

The study considered a sample period from January 1977 to January 1993 using the cross-section of shares listed on the NYSE, AMEX and NASDAQ. In every month of the sample period, portfolios were sorted independently on earnings and share price momentum, where shares were sorted into one of ten deciles. Portfolios returns were calculated on an equally weighted basis. For price momentum, the estimation period used was six months while for the earnings momentum sorts, three types of earnings news were used namely; standardized unexpected earnings (SUE), cumulative abnormal returns around the earnings date (CAR) and lastly, the six month moving average of past changes in earnings forecasts by analysts (REV6). In order to mitigate the effects of bid-ask bounce and microstructure effects, the first five days post portfolio formations were skipped for both the price and earnings momentum portfolios. In the univariate analysis, correlation analysis was conducted using the price and earnings momentum strategies. Interestingly, none of the momentum strategies were highly correlated, even in and between the earnings momentum strategies. In order to determine the drivers of price momentum, the authors considered characteristics of the decile price momentum portfolios in terms of book-to-market and cash flow-to-price as well as the average earnings momentum measures considered. The findings indicated that winner shares tended to be glamour shares in terms of the value proxies considered. Importantly, there seemed to be a positive relationship between the past earnings performance and price momentum as there seemed to be significant variation in terms of all the earnings momentum proxies (SUE, CAR and REV6) when moving from historical winners to historical losers.

When conducting similar sorts based on earnings momentum, the authors found that even though price and earnings momentum both yield significant profits, price momentum tended to be more pronounced and persisted for longer periods of time post portfolio construction. The univariate results were therefore in favor of underreaction to recent news as both the market and analysts seemed slow to incorporate information fully regarding prices and earnings. In order to determine the independence (or lack thereof) of the differing forms of momentum, multivariate sorts were conducted where shares were sorted independently into nine portfolios based on price and earnings momentum. The results of the bivariate sort indicated that momentum in share prices is

different to earnings momentum as returns of the combined strategies resulted in increased excess returns, significantly greater than returns achieved in univariate simulations. The results therefore indicated that neither momentum strategy subsumed the other, implying that the behavioral explanation that relates both earnings and price momentum to differing aspects of information is most plausible. Lastly, the authors also found that reversals in both momentum strategies seemed to occur approximately one year post portfolio formation, implying that both earnings and price momentum where both partially driven by positive feedback due to underreaction to recent information.

Barberis, Shleifer and Vishny (1998) attempted to develop a parsimonious model for investor sentiment in order to explain momentum and long-term reversal on the basis of underreaction and overreaction. Underreaction was the general behavioral explanation offered for the occurrence and persistence of momentum in share prices. The underreaction hypothesis implies that market participants tend to incorporate news into asset prices slower than that which is considered rational under the efficient market hypothesis, leading to significant positive autocorrelation in share returns. The authors noted that a core flaw in the risk based argument for the occurrence of momentum and long-term reversal is that investors can still earn superior returns while bearing minimal amounts of conventionally measured risk. The behavioral model developed encompassed two phenomena described in psychology, namely ‘conservatism’ and ‘representativeness’.

‘Conservatism’ was largely discussed by Edwards (1968) where the hypothesis implies that individuals are slow to update their beliefs even when presented with new information. Edwards found that individuals do update their beliefs in the correct direction when presented with new information, however the magnitude of the update was significantly lower when compared to the rational Bayesian benchmark. Further, it was found that the more significant (i.e. important) the information, the lower the revision of expectations. ‘Conservatism’ was therefore used by the authors to explain the occurrence of momentum in share prices, specifically the positive autocorrelation experienced that results in winner shares outperforming loser shares over the medium term horizon. The implication was therefore that market participants tend to underweight the importance of current information while being fixated on historical information. Since the process of incorporating such information is an elongated process, market participants continuously update their asset valuations, either driving up or down asset prices resulting medium term momentum.

The second psychological concept used was the representativeness heuristic of Tversky and Kahneman (1974). The representativeness heuristic implies that individuals create associations and overstate the probability of an occurrence even when historical occurrences are completely random. The representativeness heuristic is applicable to reversal in share prices over the long-

term as investors are prone to assuming that since assets have delivered significantly positive returns through time, such assets will continue to do so *ad infinitum*, even if the historical strong winning streak is solely attributable to luck. Griffin and Tversky (1992) attempted to reconcile conservatism with representativeness by developing a framework that allowed individuals to update their beliefs based on the 'strength' and 'weight' of the new information. Strength related to the importance of the information while weight referred to the importance of the source or statistical informativeness. Griffin and Tversky (1992) conjectured that conservatism would arise when individuals are faced with information with high weight and low strength as individuals react gradually due to the low strength of the information and thereby negate the high weight of the information. Conversely, representativeness is expected to arise when information has high strength but low weight as individuals overweight the strength of the information but fail to consider the bigger picture in terms of the low weight.

The authors created a model that that incorporated assumptions based on both the conservatism and representativeness hypotheses. The basic model considered a single investor that maintained risk-neutral beliefs that aligned to market consensus. Further, the hypothetical market only contains a single security that pays out total earnings as dividends and the price of the security was based on the present value of future dividends based on the expectations of the single risk-neutral investor. The model assumes that earnings follow a random walk but, as noted by the authors, the core assumption is that the investor does not consider earnings to follow a random walk, rather that earnings are governed by a binary system where one state implies trending and the other mean reverting. Considering the trending state, an investor with the belief that such a state is currently in place will make decisions consistent with the representative heuristic, implying that a revision in the investors' expectations is unlikely even when faced with new information. When the state is mean reverting in nature, the investors valuation will consistent with conservatism as the investor is expected reversion to the mean even though new data may dictate otherwise, thereby leading to the slow incorporation of information into valuations, be it positive or negative.

In order to test the hypothetical framework, simulations were conducted using a number of set parameters determining the regime switching probabilities (between trending and mean reverting) and assuming that prices were determined by the single agent with such beliefs even though earnings (which directly drive prices) follow a random walk. The authors found that returns display the patterns predicted in terms of conservatism as the average return post a positive shock was significantly higher than that of a negative shock, consistent with momentum and underreaction. Similarly, as the number of repeated earnings shocks increased for any of the simulated assets, the returns of the assets became negative implying reversal and consistent with representativeness and overreaction. Notably, even though the simulated results were consistent

with momentum and long-term reversal, the simulated returns were significantly lower than the empirical results achieved on actual share price data.

Daniel, Hirshleifer and Subrahmanyam (1998) proposed a theory that intended to explain under and overreaction in share prices, in effect developing a theory that parsimoniously explained the presence of momentum and long-term reversal in share prices over the short, medium and long term. In order to explain both phenomena, two psychological biases were used, namely: 'overconfidence' and 'biased self-attribution'. The authors highlighted a number significant challenges noted in financial literature that are not explained by efficient market hypothesis and therefore the risk-return relationship. In summary, earnings momentum, share price momentum, long term reversal and excess volatility in prices relative to fundamentals cannot be explained on a risk basis, necessitating the advent of an encompassing theory that explains the occurrence and consistency of such phenomena.

A central theme of the study as well as a core attribute that explains momentum, long-term reversal and excess volatility is overconfidence. The model proposes that individuals are more confident regarding their assessments of reality and therefore downward bias their forecast error variances. The second psychological theory is directly related overreaction, but extends the theory to self-validation, otherwise known as biased self-attribution. Biased self-attribution entails that investor's overconfidence is increased when public information conforms to their private information but the decrease in confidence is not matched when public information is contradictory. This implies that investors tend to acknowledge successes as personal but blame failures on external forces.

The basic model developed uses both overconfidence and bias self-attribution through the development of a market that contains two types of agents separated into two groups, one which receives information in the form of a signal and those that don't. The model assumes that the informed investors are risk-neutral while the uninformed are risk-averse. The model assumes that there are four dates, where at date 0, each agent holds a basket of securities and all have identical prior beliefs. At date 1, the informed set of traders are differentiated as they receive a noisy information signal regarding the value of a security and begin trading on the information with the uninformed investors. At date 2, a noisy public signal arrives that is disseminated to both the informed and uninformed agents and further trading occurs. At the final date, conclusive (non-noisy) public information arrives, the security pays a liquidating dividend and consumption occurs. A key point is the noisiness of the information received by the informed investors at time 1 and the public at time 2. Considering the information at time period one, informed traders only receive the information, but they consistently underestimate the variation of the precision of the information.

Using the model described above, average price paths were described following the types of signals received by informed individuals. When there is overconfidence regarding the private signal, share prices will overreact to the new information. In a static confidence setting, the model predicts that public noisy information at date 2 will result in a correction to prices, implying that initial momentum is reversed and therefore there is negative autocorrelation between periods 1 and 2. At the final date, correct and final information is delivered to the market resulting in a correction to prices, implying positive autocorrelation over periods 2 and 3. The result is therefore consistent with long-term reversal and the correction in share prices. The study then allows for bias self-attribution by assuming that confidence levels are variable as opposed to static. This implies that confidence can vary when private information is either consistent or inconsistent with public noisy information. The authors referred to time periods 0 to 2 as the overreaction phase and indicated that the allowance of updating confidence results in significant positive autocorrelation during the overconfidence phase. The repetition of public information that is less noisy results in the share price being driven back to fundamental values.

In order to qualify the results of the proposed model, simulations were conducted that allowed for an arbitrary number of periods and share price simulations. Initially, simulations were run assuming that the private noisy signal was highly favorable, where the price value was initially set at zero. The simulation analysis indicated that the simulated share price initially increased to 0.5 and reached a peak of 0.76 at 16 periods and thereafter decreased asymptotically to zero 60 periods post the private information release. The inclusion of the self-attribution bias allows for both momentum (positive autocorrelation in short-term returns) in share prices and long-term reversal (long-term return negative autocorrelation). Notably, the assumption of overconfidence alone only produces long-term reversal in share prices. The results of simulations confirmed that two phenomena that circumvent risk explanations are possibly clarified via the psychological concept of self-attribution bias, which is inextricably linked to overconfidence.

Hong and Stein (1999) considered a differing set of behavioral biases and assumptions in attempt to disentangle the momentum and long-term reversal found in share prices. The authors first acknowledged the failure of risk based explanations ability in decomposing stylized investment criteria implying theoretical room for the development of further theory that explained both momentum and long-term reversal. Following Fama (1998), a plausible theory required three core attributes namely; based on noted or observed psychological phenomena, explained the current evidence and lastly, can be tested out-of-sample. The authors acknowledged that their approach differed significantly from Barberis *et al.* (1998) and Daniel *et al.* (1998) as both studies made assumptions regarding the representative agents as opposed to the interaction between groups of agents. The model developed considered two groups of agents that differed based on their classification as “newswatchers” and “momentum traders”. Both sets of market participants were assumed to be rational in the sense that different agents were able to process certain subsets of

publicly available information. The implication is that “newswatchers” make decisions based on signals that they privately observe and directly relate to fundamentals of the asset. Conversely, momentum traders condition their beliefs solely on past prices. The final assumption made was that private information is diffused gradually across the news watcher agents.

The authors consider the potential drivers of momentum (underreaction) and overreaction (long-term reversal) in share prices. In consideration of underreaction, the study refers to the rate of information diffusion while long-term reversal is largely based on overreaction where good news shocks results in share prices overshooting their fundamental values, eventually resulting in a correction. The model is initially described considering only “newswatchers”, where each agent trades assets whose value is based on a single liquidating dividend at a future date. In order to reflect slow information diffusion, the “newswatcher” population was stratified into a number of groups where innovations in dividend changes are then incorporated into the groups, based on which group the “newswatchers” form part of. The groups then shift at each future time period, where the first group is now the last group from the previous information diffusion occurrence, allowing each group to get a chance in receiving the private information first while still allowing for the information to be incorporated slowly. The implication of the process is that at a certain time-period in the future, the information regarding the dividend information has been fully incorporated by the “newswatchers”.

The model then incorporates the “momentum traders” who are assumed to have finite horizons and therefore at each time-period, a new set of momentum traders is introduced to the fictional economy. The momentum traders trade with the “newswatchers” and are assumed to make univariate forecasts solely conditioned on past information in prices. The authors found when conducting simulation analysis and applying the parameters of the model, when “newswatchers” are present, prices tend to underreact to information, implying the creation of momentum opportunities represented by momentum profits in asset prices. More importantly, when introducing “momentum traders” that trade solely on univariate price based information, a portion of the underreaction is corrected but also results in overreaction, driving share prices beyond their true fundamental values. The implication of the model is a unified behavioral theory that implies that underreaction is not only a pre-cursor to overreaction but is a pre-condition. The core assumption to the model is a single condition of slow diffusion of information into share prices. The model and theoretical framework is therefore consistent with the large number of findings pertaining to momentum, size and analyst coverage, where greater mispricing is expected in less covered, less liquid shares. The simulation results indicated that the model meets the criteria regarding the formulation of alternate asset pricing theories, specifically in that it is based on a simplistic behavioral assumption, it is parsimonious and it predicts that which is seen in real data regarding stylized investments generating abnormal returns.

Baker and Wurgler (2006) considered the effects of investor sentiment on the cross-section of stock returns listed on the CRSP database over the period January 1926 to December 2001. The central hypothesis of the study asserted that the cross-sectional variation in share returns is poorly explained by risk loadings and rather by variations in investor sentiment that lead to systematic mispricing. The study considered multiple definitions of sentiment where sentiment is defined as the "propensity to speculate", therefore a driver of demand for speculative investments. Speculative investments refer to investments with higher information asymmetries, lower dividends and shorter earnings history while non-speculative investments follow safer cash cow type shares with long earnings histories and high historical dividend payout ratios. For the purposes of simplification, the authors further defined sentiment as the current state of emotion towards both the economy and share markets.

In order to empirically test the possibility of sentiment effecting the cross-sectional variation in returns, the study considers a model that attempts to identify systematic patterns of correction of mispricing's through conditional patterns in cross-sectional return predictability. This was done by using a model that considers a vector of security characteristics as well as a time-series proxy for investor sentiment. The basic test considered whether the coefficient on the lagged sentiment variable is statistically different from zero, implying that mispricing is corrected and that sentiment drives cross-sectional variability in returns. In total, six proxies for investor sentiment were used and included closed-end fund discount, NYSE turnover, first day IPO returns, equity share in new issues and dividend premium. In order to remove market cycle effects, the authors orthoganalised each of the sentiment proxies on several macroeconomic variables and used the regression residuals as time-series proxies for sentiment.

To test the effects of sentiment on cross-sectional variation, shares were sorted monthly into categories based on characteristics such as size, value and momentum in share prices and simultaneously on the level of sentiment proxy from the previous year. The dual sorting procedure produced results implying that investor sentiment affected return variation even when initially sorting on share characteristics, indicating that sentiment has a positive relationship with earnings, dividends and momentum implying that all characteristics produce superior returns when conditioning on market wide sentiment proxies. In order to further test the robustness of results, Fama-Macbeth style regressions were run were a four factor model, which included momentum, was utilized to define factor premia using monthly returns. The coefficients were then further tested in order to determine whether the incorporation of a sentiment proxy led to a variation in factor premia. The findings indicated that, irrespective of the proxy used for sentiment, the sentiment factor added to the premium of the explanatory variables considered, even momentum. This implies that over the sample period, investor sentiment explained a portion of the returns earned using popularized styles. This implies that a systematic behavioral bias that

tends to create demand shocks influences the cross-section of expected returns, lending credence to a behavioral explanation behind the data generating process of share returns.

As previously described, Chui, Titman and Wei (2010) conducted an empirical study into the effects of behavioral biases on momentum profits. The study considered a proxy for individualism, credited to Hofstede (2001), and attempted to prove the behavioral theories developed by Daniel *et al*. (1998), Barberis *et al*. (1998) and Hong and Stein (1999). The central hypothesis of the study was to determine whether momentum profits were greater in countries that exhibited greater levels of individualism, as individualism has been related to overconfidence and bias self-attribution. Individualism refers to a cultural collectivism that was described by Hofstede (2001) as an "independent self-construct". The inverse of such a construct is referred to as collectivism, which implies a collective need for lack of differentiation and social connection. The link between individualism and overreaction or self-attribution bias was not a unique concept and was supported by psychological literature. Markus and Kitayama (1991) found that cultural individualism was highly correlated with self-belief and focus on internal attributes. Heine *et al*. (1999) found that individualistic cultures resulted in above average belief in their own abilities and the inverse in collectivistic cultures. Zuckerman (1979) considered a link between individualism and bias-self attribution, asserting that individualism is directly related a tendency to take undue credit and deny responsibility for failure.

In order to test the effects of individualism on momentum returns, the study considered the effects of culture on momentum returns, therefore empirically testing the effects of individualism on momentum profits. Further, the authors also considered other manifestations of behavioral biases that are considered an effect of overreaction and self-attribution bias, namely excess trading volume and idiosyncratic risk. Therefore, the central hypothesis implied testing momentum profits across individualistic and collectivistic markets. Using the Hofstede individualism index, factor analysis was implemented in order to extract principal components where the first factor was used to create new individualism scores. Share price data for 55 countries over the period February 1980 to June 2003 was used to form momentum portfolios. Initial tests were considered attempting to relate the cross-sectional differences in country specific trading volume and excess volatility to individualism. Odean (1998), Gervais and Odean (2001) and Daniel *et al*. (1998) all theoretically proved that the behavioral biases that lead to momentum in share prices invariably also cause excess volatility and high levels of liquidity typically produced by the extreme trading conducted by overconfident investors prone to self-attribution bias.

In order to test whether individualism affects turnover and volatility, regression analysis was conducted that set the natural log of country turnover and volatility as the dependent variable and used a number of independent variables that have been empirically linked to drive volume and volatility. In both regressions, an individualism variable was included in order to determine

whether there was a causal link between individualism (i.e. overconfidence and self-attribution bias) with volatility and volume. The results of the regression analysis indicated that even when controlling for other determinants of trading volume and volatility, the individualism variable produced a significantly positive coefficients, implying that individualism or the hypothesized behavioral biases that lead to momentum, explain a portion of the cross-sectional differences in volatility and volume on a country level.

In attempt to determine whether individualism explains the country level differences in momentum profits, country momentum portfolios were sorted assuming a six month holding and estimation period allowing for a one month gap between portfolio estimation and investment. In order to account for the potentially low number of shares in certain markets, tercile splits were used. Of the 41 countries considered, 25 countries experienced significantly positive momentum, 12 positive insignificant momentum while four achieved produced no evidence of momentum in equity index prices. The four countries that did not display any form of momentum were Turkey, Korea, Taiwan and Japan. In order to test for a relationship between momentum and individualism, countries were sorted into one of three categories based on their Hofstede scores. Momentum portfolios were then formed within the three categories, effectively emulating a dual dependent sort on individualism and then momentum. The results indicated that momentum profits maintained a positive relationship with individualism as the high individualism momentum portfolios achieved a significant excess return of 0.65% per month over their low individualism counterparts and the difference was significant at the 5% level.

In order to qualify the results of the bivariate dependent sorts, regression analysis was conducted on the country momentum portfolios were momentum returns were regressed on individualism as well as other variables that could possibly explain the momentum phenomenon, grouped into categories of time-invariant and time-updating explanatory variables. The findings of the regression analysis indicated that individualism was a significant determinant of momentum and specifically explained the cross-country variation in geographical momentum premiums. In order to control for the cross-sectional differences in market development and integrity, a further set of regressions were run that included a market development and integrity proxy based on the natural logarithm of GDP.

The results of the second regression analysis indicated that individualism was still a significant determinant even after controlling for market development and integrity. A number of further robustness checks were considered where additional variables were added to the regression analysis, specifically where a different individualism index was used and further cultural variables were added. The findings were consistently in favor of individualism explaining the cross-sectional differences in global momentum premia. The results of the study indicated that the theoretical behavioral hypotheses that were developed to explain momentum in share prices had empirical

merit as momentum profits globally were proven to be sensitive to variations in individualism, which is expected to be highly (and positively) correlated with overconfidence and self-attribution bias.

2.3.2 Limits to arbitrage

A corollary to the efficient market hypothesis emerged that amalgamates the efficient market hypothesis with behavioral connotations regarding arbitrageurs. The hypothesis allows for a unified explanation behind the continued existence of mispricing anomalies within a risk based framework. Arbitrageurs play a central role in the efficient market hypothesis as they are expected to correct the emergence of mispricing by trading on their superior information. If arbitrageurs are prevented from engaging in arbitrage and are therefore unable counteract the effects of mispricing, a possible cause for the persistence of systematic mispricing emerges.

Shleifer and Vishny (1997) considered the practical difficulties of conducting arbitrage, specifically the inherent risks related to the capital requirements and leverage. The authors presented a dynamic of arbitrageurs being only a small subset of the investment community whose capital funds are sponsored. The natural outcome of the sponsorship of capital leads to an agency relationship, which is a further limit to arbitrage. The authors developed a model that theoretically proves that the presence of arbitrageurs or “smart money” may actually lead to further divergence of prices from fundamentals in the presence of arbitrage opportunities. Further, the study also presents a negative relationship between the presence of arbitrage and idiosyncratic risk. The argument seems almost counterintuitive as logically; increased volatility should lead to greater levels of mispricing and therefore greater arbitrage opportunities. The model implies that increased volatility would result in arbitrageurs being reluctant to short highly volatile assets.

The authors related the example to the value phenomenon and its continued existence through time. Considering Fama and French (1992), the existence of the value phenomenon is only realized over relatively longer holding periods (12 months) and the shorting portfolio are popular growth or glamour shares. Coupled with this is the ‘truer’ notion that arbitrageurs are a select, semi-constrained and risk averse group, the anomaly persists as there is extreme volatility inherent in engaging in a pure arbitrage strategy to eliminate the value phenomenon. The study therefore provided a testable hypothesis regarding the presence of anomalies and their persistence, tying their presence to the specific idiosyncratic risk of the assets or anomalies in question.

Lesmond, Schill and Zhou (2004) explored the limits to arbitrage argument and specifically focused on direct transaction costs and their ability to limit arbitrage, thereby creating room for anomalous mispricing to emerge and persist. The core hypothesis of the study centered on the

presence of momentum in share prices and that momentum is largely found in shares with cross-sectionally higher trading costs. The implication is that the momentum premium persists as trading costs deter arbitrageurs from engaging in momentum strategies. Applying the methodology of Jegadeesh and Titman (1993), momentum portfolios were sorted using US share return data over the period January 1980 to December 1998. The authors applied a rolling six month estimation period, implying that overlapping momentum portfolios were sorted on a monthly basis using a six month estimation period and held for equivalent periods post estimation.

Differing from Jegadeesh and Titman (1993), shares were sorted into one of three equally weighted portfolios. The lower number of portfolio stratums did not negatively affect momentum results as the excess return achieved over the sample period was 0.88% per month and significant at the 5% level. Consistent with previous momentum studies, the authors noted that a large proportion of momentum profits are derived from the short position in the loser portfolio. Using both regression and portfolio sorts, evidence was presented that found that the short position in the loser portfolio provided approximately 67% of the excess return produced in the results presented by Jegadeesh and Titman (1993).

The authors then evaluated the transaction cost proxy used by Jegadeesh and Titman (1993) and hypothesized that the proxy applied significantly understated the potential transaction costs borne when engaging in momentum strategies. Considering the types of shares found in the extreme portfolios; shares had cross-sectionally higher betas, lower prices and market capitalizations and were generally not listed on NYSE. In order to analyze the liquidity of shares within the momentum portfolios, the number of zero daily return occurrences were measured for all shares cross-sectionally. Loser shares were found to be significantly less liquid over the sample period, achieving a zero daily return rate of 30%, significantly larger than the shares within the medium and extreme winner portfolios. In order to proxy transaction costs, the study made use of four trading cost measures in order to test the hypothesis of transaction costs causing momentum in share prices to persist. The four trading costs measures were the bid-ask spread, Roll (1984) spread, commission estimate and lastly, the LDV estimate of Lesmond *et al.* (1999). For each share considered in the momentum portfolio simulations, the four transaction cost measures and the effective costs of a round-trip transaction were estimated. The basis of the test considered whether momentum profits outperformed the costs incurred by engaging in the said strategies.

The results of estimating the round-trip transaction costs for the extreme momentum portfolios indicated that the extreme portfolios experience significantly higher proportional transaction costs than the middle portfolio. The implication of the finding rejects the notion that shares within the portfolios has similar trading costs. In order to determine the returns ex-post the effect of transaction costs, simulations were re-run with the application of the various trading cost measures. When applying the LDV cost measure, the estimated cost associated with a six month

estimation and holding period momentum arbitrage strategy results in costs of 0.94% per month, entailing a net loss attributable to the strategy of -1.5% per annum. In order to add further robustness, the authors acknowledged that a round-trip transaction may not be the appropriate assumption as some shares may be winners or losers for more than a single period, implying that no transaction is required in a particular month (or any holding period applied).

The authors found that the number of shares retained in the same portfolio over the next holding period tended to be 23% for winner shares and 15% for losers. In order to remove the effects of the over-trading bias, transaction costs were revised down in proportion to the expected continued holding. The total costs associated with implementing a momentum arbitrage strategy dropped to 7.7% per annum while the estimated profit increased to 0.1%. The authors therefore concluded that momentum profits net of transaction costs were not significantly positive as depicted in the numerous studies that found evidence of the momentum effect. The findings of the study cast doubt on the consistency of momentum profits, dubbed as 'illusory' by the authors, but more importantly, potentially provide a possible explanation in momentum persistence due to the inability or constraints experienced by arbitrageurs in implementing momentum strategies, specifically related to transaction costs.

Pontiff (2006) presented an argument pertaining to the debunking of several myths related to the limits to arbitrage hypothesis. The essence of the study emphasized that the costs of engaging in arbitrage can be separated into transaction costs, i.e. costs associated directly with the action of arbitrage and holding costs, which is largely made up of idiosyncratic risk. Core to the presence of efficiency is that prices reflect available information and that rational agents (assuming there is a group of rational agents) can achieve profit from engaging in arbitrage, thereby removing the effects of mispricing. The logical pattern leads to the limits to arbitrage hypothesis, where rational traders require profits in excess of costs in order to trade on mispricing. Pontiff (1996, 2006) defines holding costs as costs associated with maintaining the arbitrage position, specifically the opportunity cost of capital, opportunity cost of not receiving interest income through the short sale position and most importantly, the idiosyncratic risk of the position. The relationship with mispricing is obviously positive for both transaction and holding costs, however, holding costs are hypothesized to be a greater component of arbitrage costs and therefore more central to determining the level and persistence of mispricing.

Importantly, the question of diversification is key to the argument of idiosyncratic risk preventing arbitragers from trading on mispricing. Pontiff (2006) offered an example explaining the limited effect of diversification on idiosyncratic risk of arbitrage positions. The author hypothesized that the number of mispriced assets does not lower the idiosyncratic risk of the said investment as idiosyncratic risk is only diversified when shared across representative agents and not mispriced securities. This implies that if a number of rational agents are engaging in the same arbitrage over

the same mispriced asset, then the idiosyncratic risk associated with trade would be diversified, however, as the author noted, engaging in arbitrage of one mispriced asset will not result in the risk of the next arbitrage transaction being reduced.

Using portfolio mathematics, the optimal position for an arbitrageur that hedges all market risk is defined as the ratio of alpha associated with the mispricing scaled by the combination of utility and idiosyncratic risk of the arbitrage position. Therefore, under a mean-variance optimization framework, an arbitrageur's position in a mispriced share is directly related to the inverse of idiosyncratic risk, implying a negative relationship between idiosyncratic risk and the size of the arbitrage position. The study concluded that even though transaction costs have received a larger portion of the focus in literature, holding costs (idiosyncratic risk) are as important in contributing to the limits to arbitrage. The author offered a powerful yet simple analogue that considers a single patron at a free buffet. Based on pure utility maximization, a patron should eat beyond his capacity since the lunch is free and portions are not modified. However, there is an associated risk that cannot be diversified which is the risk of severe heartburn and nausea through overeating. The analogue is related to the effects of idiosyncratic risk associated with the arbitrage position. The position or size of the trade is directly impacted by the idiosyncratic risk associated with holding the position, which directly affects the ability of arbitrageurs to remove the effects of mispricing as the marginal profits associated with arbitrage are not guaranteed to offset the marginal costs of engaging in arbitrage.

McLean (2010) considered the "limits to arbitrage" argument of Pontiff (2006) by testing the effects of transaction costs (both direct and indirect) on momentum and long-term reversal strategies. Like Pontiff (2006), the study focused on the effects of idiosyncratic risk on return performance. Portfolio sorts were conducted on the cross-section of shares listed on the CRSP and Compustat databases over the period January 1965 to December 2004. Shares with less than 36 monthly consecutive returns were excluded from the sample. Initially, shares were sorted into quintiles based on reversal, momentum and idiosyncratic risk. Reversal quintiles were formed using the historical three year return (36 months) skipping the most recent six months while momentum portfolios were formed using the historical six month cumulative returns, skipping the most recent month in order to minimize the effects of bid-ask bounce. Idiosyncratic risk was calculated as the monthly return variance orthogonal on the S&P 500 measured over the previous 36 months. Shares were sorted monthly into quintiles and held for 12 months post sort, allowing for overlapping monthly portfolio returns to be estimated over the sample period.

In both momentum and long-term reversal sorts, winner and loser shares maintained high levels of idiosyncratic risk when compared with other quintiles. The findings are robust to three methods used for defining idiosyncratic risk, including a 5 factor model, which is an augmented Carhart model with an industry factor and future idiosyncratic risk that is idiosyncratic risk calculated over

the future 36 months. In order to proxy for transaction costs, both the Gibbs measure described by Roll (1984) and the illiquidity measure of Amihud (2002) were used. When considering long-term reversal, both transaction cost proxies were far higher for long-term losers than for long-term winners. The results of the momentum portfolio sorts were slightly different as both momentum winners and losers produced high transaction cost measures.

The results of the idiosyncratic risk sorts indicated that idiosyncratic risk is persistent in quintiles as the high idiosyncratic risk quintile achieved idiosyncratic risk that was 22 times higher than the low idiosyncratic risk portfolio. Considering the argument of Pontiff (2006), this would imply that an arbitrageur would provide 22 times more capital for investment in the low idiosyncratic risk portfolio. Furthermore, the results indicated that idiosyncratic risk is positively related to direct transaction costs as both the illiquidity measure and Gibbs cost increase monotonically when moving from low to high idiosyncratic risk quintiles. Lastly, when considering the correlation between the various measures of idiosyncratic risk, the resulting correlations in terms of rank was 80% but substantially weaker when measured in terms of actual idiosyncratic risk. Importantly, barring the poor correlation in actual variance measures, the fact that ranking remained consistent implies that shares exhibit idiosyncratic risk persistence irrespective of the precision of the idiosyncratic risk measures.

In order to test the effects of idiosyncratic risks on results, varying weighting schematics were applied to determine the effects of arbitrage holding costs on arbitrage profits, specifically related to momentum and long-term reversal sorted portfolios. Portfolio returns were computed using four weighting schematics, namely equal weighting, value weighting, idiosyncratic risk weighting and the inverse of idiosyncratic risk weighting. Portfolio returns were calculated over six month holding periods and cross-sectional equally weighted overlapping portfolio returns were combined to determine a single months returns. For each style, excess return premia were calculated, implying long-term loser share returns minus their winner counterparts and six month winner shares minus their loser counterparts. The results of the reversal portfolios indicated that long-term reversal maintains a positive relationship with idiosyncratic risk as reversal returns were greatest when weighting based on idiosyncratic risk, achieving excess returns of 1.4% per month and a significant 3 factor alpha. Conversely, when weighting constituent shares on the inverse of idiosyncratic risk, both the gross excess return and three factor alpha were insignificantly different from zero.

Consistent with international literature, the results indicated that momentum profits were significant when using equal weighting, achieving significant excess profits of 0.74% per month over the sample period. Value weighting resulted in momentum returns increasing to 0.88% per month, where excess returns were enhanced by poorer returns achieved by losers when measured on a value weighted basis. Contrary to the results of the long-term reversal portfolios,

idiosyncratic risk weighting resulted in insignificant excess returns of 0.375% per month while the inverse of idiosyncratic risk achieved excess returns of 0.716% per month, and were significant at the 5% level. The results of the momentum sorts varied significantly to those of the long-term reversal as idiosyncratic risk seemed to have minimal effects of momentum returns, implying that arbitrage holding costs fail to explain the magnitude and persistence of momentum.

Conversely, long-term reversal maintains a significantly positive relationship with idiosyncratic risk, implying that a possible cause for the persistence of long-term reversal is that arbitrageurs are limited by the inherent idiosyncratic risk of the strategy, resulting in the persistence of the mispricing through time. In order to add robustness to the tests conducted, all tests were re-run while excluding shares based on price and market capitalization. The results of reversal were virtually unchanged as the reversal premium was only present in the two highest idiosyncratic risk quartiles, implying that the positive relationship was not driven by small low priced shares. When applying the exclusions to the momentum portfolios, momentum premia were largely unchanged as momentum profits seemed to bear no significant relationship with idiosyncratic risk.

Consistent with the previous results noted in value weighted sorts, the exclusion of small and low priced shares improved the results of the momentum sorts where even the highest idiosyncratic weighted momentum portfolio achieved average excess returns of approximately 1%. The results of the study provided evidence in favor of the limits to arbitrage theory explaining the persistence and magnitude of excess returns for the long-term reversal phenomenon, but failed to do so for momentum in share prices. The natural conclusion was that holding costs (idiosyncratic risk) fail to explain momentum persistence, implying that holding costs are not the cost driver preventing arbitrageurs from trading away momentum. The study concluded that the persistence of momentum is probably attributable to direct transaction costs, a further limit to arbitrage and cast dispersions on single unifying behavioral theories of Barberis *et al.* (1998), Daniel *et al.* (1998) and Hong and Stein (1999) that predict momentum and long-term reversal in share prices. The implication of long-term reversal and momentum not being sensitive to identical limits to arbitrage provides evidence of both premiums (mispricing's) being driven by differing data generating processes.

Contrary to the findings of McLean (2010), Brav, Heaton and Li (2010) found limited evidence in favor of the limits to arbitrage hypothesis. The sample covered all shares listed on the NYSE, AMEX and NASDAQ over the period July 1958 to December 2007. Idiosyncratic risk was measured as orthogonal to a Carhart four factor model over the period. Initial tests involved dual sorting of shares based on a certain characteristic and residual variability (idiosyncratic risk). Sorting initially on size, the largest size effect was found in the lowest idiosyncratic risk quartile, implying that idiosyncratic risk as a limit to arbitrage fails to explain the size effect. The results held true when considering varying alphas. Considering the pure CAPM model results, the high

idiosyncratic risk small-size portfolio did not achieve a significant alpha but time-series alphas increased monotonically (in terms of t-statistics and economically) when moving to the lower idiosyncratic risk quartiles. Similarly, when considering the value phenomenon, the limits to arbitrage hypothesis seemed to apply to growth shares. The authors found that the high idiosyncratic risk value portfolio achieved insignificant alphas, irrespective of the model used. Like the size phenomenon, the value effect is only prominent in the lowest idiosyncratic risk quartiles.

Momentum portfolio returns were defined using 12 month estimation period excluding the most recent month in order to reduce the effects of bid-ask bounce. Consistent with the results of size and value, the momentum premium was lowest in the highest idiosyncratic risk quartile. Using the pure CAPM model, the winner portfolio achieved an insignificant alpha of 0.14% per month while the low idiosyncratic risk winner portfolio alpha was 0.36% per month and significant at the 5% level. The final set of tests considered a combined value and momentum strategy where value is conditioned on past momentum. The test arises from the findings of Barberis and Thaler (2003), where the authors hypothesized that value shares that exhibit recent loser momentum should exhibit greater future value returns as arbitrageurs are reluctant to invest in arbitrage strategies that can possibly further diverge from fundamentals. The tests are in effect similar to initial tests as further divergence from fundamentals is possibly exacerbated by the idiosyncratic risk of the underlying asset.

Therefore, the in-value momentum applied to a value strategy indicates the direction of divergence as opposed to the range. The results of the dual sort on value and momentum produce results inconsistent with those predicted by the limits to arbitrage hypothesis as the winner-value portfolios significantly outperformed the loser value portfolios by 0.8% per month on average. The results of the study cast doubt on the findings of McLean (2010) as value and long-term reversal tend to be highly correlated as shown by Asness *et al*. (2013). McLean (2010) found that the limits to arbitrage hypothesis applies to value or long-term reversal and not momentum, which is contrary to the findings of Brav *et al*. (2010). Importantly, both studies were consistent in terms of the momentum premium, which seems impervious to the effects of idiosyncratic risk limiting arbitrage and thereby failing to explain the persistence of momentum in share prices.

Page, Britten and Auret (2016) evaluated the limits to arbitrage hypothesis on the cross-section of shares listed on the JSE over the period January 1992 to November 2014. Based on the study of McLean (2010), the authors intended to determine whether direct or indirect transaction costs explained size, value or momentum on the JSE. In order to determine the effects of direct transaction costs, shares were sorted on market capitalization, book-to-market ratio and historical 12 minus one month historical returns and while simultaneously applying price and liquidity filters. Price filters were referred to as direct trading costs while liquidity filters indirect trading costs. The results indicated that value returns seemed far more sensitive to direct trading costs while the

opposite was found for momentum. In order to evaluate the effects of holding costs, the authors applied T-GARCH and GARCH-in-the-mean tests to the size, value and momentum premium.

The application of GARCH models allowed for the analysis of factor premia in terms of their univariate idiosyncratic risk, specifically whether shocks to the respective premiums was asymmetric and whether increases in idiosyncratic risk were met with corresponding increases in unconditional mean return. The GARCH analysis produced results that were largely consistent with the findings of McLean (2010). The value premium results indicated that a positive increase in conditional variance was met with a significant increase in excess return, implying a positive relationship between value and idiosyncratic risk. Conversely, the momentum premium tended to react negatively to increases in conditional variance, implying a negative relationship between the momentum premium and idiosyncratic risk. The authors therefore concluded that the limits to arbitrage argument, specifically holding costs as a limit to arbitrage, apply to value and not momentum on the cross-section of shares listed on the JSE.

2.3.3 Risk based explanations of momentum in share prices

The majority of momentum studies indicate that the momentum premium cannot be explained via conventional risk proxies. Jegadeesh and Titman (1993) found that momentum could not be explained by size or beta, pointing to behavioral theories as the most plausible explanation of the phenomenon. The discovery and presence of a consistently positive and significant momentum premium is (further) evidence negating the validity of the EMH, CAPM and market beta. Given the inadequacy of market risk in explaining beta, a number of studies attempted to determine whether the momentum premium is explainable using other risk based explanations (and proxies). The review of literature that follows considers studies that rely on theories and hypotheses that are bounded by the assumptions of rationality and return being driven by underlying risk. Fama and French (1996) considered a number of noted pricing anomalies that featured in recent literature as significant contradictions of the CAPM model. The Fama-French three factor model, first described in Fama and French (1993), assumed that since value and size premia are persistent, the CAPM should be augmented to include the noted premia as risk factors.

The central hypothesis of the study argued that the Fama-French three factor model was capable of describing systematic mispricing as all noted anomalies are inter-related. Initially, 25 size and value sorted portfolios were estimated using the cross-section of shares listed on the NYSE, AMEX and Nasdaq exchanges over the period June 1963 to June 1993. Applying the Fama-French 3 factor model, time-series regressions were run and time-series alphas were jointly tested using the GRS statistic. Consistent with the findings of Fama and French (1993), the GRS statistic indicated that alphas are not distinguishable from zero while the average R^2 of the regressions

was 92%, indicating that the model performed well in explaining the variation in returns of the dual sorted portfolios.

The second set of empirical tests related to the decile sorts conducted by Lakonishok, Shleifer and Vishny (1994), where portfolios were sorted into deciles based on book-to-market, earnings yield, cash flow-to-price and five year sales rank (referred to as LSV portfolios). Like the results of Lakonishok *et al*. (1994), the authors found a significantly positive relationship between expected returns and the book-to-market, cash flow-to-price and earning yield ratio and a significantly negative relationship with past sales growth. The LSV portfolio time-series returns were then mapped using Fama-French three factor models over the sample period. The results were more convincing when compared to the 25 size-value sorted portfolios. The GRS statistic rejected the null of the portfolio alphas being jointly significantly different from zero, while the average R^2 of the time-series regressions was 92%. The final set of tests considered portfolios sorted on past returns, implying sorts based on long-term and short-term winners and losers, thereby testing the findings of De Bondt and Thaler (1983, 1985) and Jegadeesh and Titman (1993). Momentum and long-term reversal portfolios were formed over the period July 1963 to December 1993 using the cross-section of shares listed on the NYSE, AMEX and NASDAQ. Shares were sorted into one of ten momentum portfolios based on the historical 12 month return, skipping the latest months return in order to account for bid-ask bounce. Long-term reversal portfolios were formed by sorting shares into deciles using the historical 60 months of returns.

The authors found a significant momentum premium over the time-period of 1.31% per month while long-term reversal achieved 1.16% per month. When applying the Fama-French three factor model, the alphas produced by the long-term reversal portfolios were not significantly different from zero as long-term loser shares loaded heavily on the size (SMB) and value (HML) factors. Conversely, the Fama-French three factor model failed to explain the momentum effect as winner portfolios always generated significantly positive alphas while losers generated significantly negative alphas. The source of the results was that loser shares tended to load positively and significantly on SMB and HML. The results indicated that the momentum premium could not be explained by the factors prescribed by Fama and French (1992, 1993 and 1995) as “state” variables and core drivers of risk.

Conrad and Kaul (1998) developed a framework for determining the source of profits attributable to momentum and long-term reversal strategies. The application of momentum and long-term reversal requires the sorting on past performance. The authors conjectured that past performance contains two components, namely a time-series predictability in returns calculated on a univariate basis and a cross-sectional differences in mean returns across shares. The central hypothesis suggests that momentum profits are due to the purchase of high mean return shares funded through the sale of low mean return shares, which should result in positive profits in the form of

excess returns contingent on the presence of cross-sectional dispersion in mean returns. In order to test the theory empirically, portfolio sorts were conducted over the period January 1926 to December 1989 using the cross-section of shares listed on the NYSE and AMEX exchanges.

Eight strategies were applied to the data using equal estimation and holding periods ranging from 1 week to 3 years. Portfolio sorts were conducted on a monthly basis assuming equally weighted overlapping portfolio returns. Applying the methodology of Lo and Mackinlay (1990), shares were assigned to portfolios based on the historical excess time-series returns measured over the estimation period. The results of the portfolio sorts indicated that of the 36 strategies implied (18 momentum and long-term reversal strategies using equivalent estimation and holding periods), 21 produced statistically significant average returns composed of 11 contrarian and 10 momentum strategies. In order to gauge the consistency of the phenomena, the sample period was stratified into time periods. The findings indicated that momentum was far more consistent across time periods and that long-term reversal was only significantly present over the 1926-1947 sub period.

After proving the existence of momentum over the period analyzed, the sources of momentum and long-term reversal profits were decomposed using a model that followed Lehmann (1990) and Lo and Mackinlay (1990) where under the assumption of mean stationary, total expected return to a strategy is assumed to be driven by time-series predictability and cross-sectional dispersion in mean returns. Jointly with the return decomposition, the authors presented a model that depicts the data generating process of share returns based on random walk (weak form EMH), implying a data generating process that contains an average return component (deterministic) and an error component (stochastic). The authors applied the model as it negates the potential profitability arising from time-series predictability and thereby simulates the effect of an efficient market.

The basis of combining the return decomposition and the assumed data generating process is to demonstrate that momentum strategies will be profitable even if asset returns are not predictable, as momentum strategies earn profits solely from buying high average return shares and shorting low average return shares. In order to test the model, the various momentum and long-term reversal portfolio profits were decomposed into time-series “predictable” return and cross-sectional components. The authors found that the cross-sectional variation component was significantly positive in explaining momentum profits over the periods considered and similarly significantly negative for the long-term reversal sorts. Further, the authors found that when quantifying the percentage contributions of time-series predictability and cross-sectional variation of mean returns, of the 18 momentum portfolios constructed over the sample period, only two depicted that cross-sectional dispersion in mean returns contributed less than 100% to total momentum profits.

Additional robustness tests were performed using Bootstrap and Monte Carlo simulations. In bootstrap simulations returns were simulated using a boot strapping methodology where actual individual share returns over the sample period were scrambled in attempt to eliminate any time-series dependence present in returns but retain other core properties present in the return data, specifically the cross-sectional average return of each of the shares considered. The bootstrapping simulation was conducted 500 times, implying the generation of 500 'new' samples on which momentum and long-term reversal portfolio sorts were conducted. The authors found that momentum strategies within the bootstrap simulated samples were still significantly high, further proving that cross-sectional variation in average returns was a significant contributor to momentum profits. Monte Carlo simulations were then conducted that utilized moments of actual returns present in the sample but applied a return generating process that mimicked a random walk. The findings of the Monte Carlo simulation results were similar to those of the bootstrapping simulations as momentum sorts achieved significantly positive returns, even though the data generating process applied to returns excluded the possibility of time-series dependence. The results of the study attacked a significant component of the rejection of the CAPM and the EMH in light of the presence of momentum. Core to the argument against CAPM is the possibility of predictability in share returns implying that since returns are predictable, there is no compensation for risk in initiating and profiting from momentum strategies. Conrad and Kaul (1998) attacked the "predictability" notion by proving that momentum profits are not borne from time-series dependence but rather cross-sectional variation in average returns, implying that momentum is in fact a compensation for some form of risk and is not merely a behaviorally induced systematic mispricing.

Carhart (1997) conducted a study on the persistence of mutual fund performance. Even though the study centered on mutual fund performance, significant risk-return themes emanated from the work, specifically the inclusion of momentum as a factor in a Fama-French asset pricing framework. Central to author's argument was whether consistent mutual fund performance is attributable to superior stock picking by managers or rather that managers merely load on common factors that explain stock returns. The study considered a database of pure equity mutual fund data that spanned over the period January 1962 to December 1993. Survivorship bias was avoided by all funds being maintained in the sample and included 1892 diversified equity funds spanning 16 109 fund years. Monthly returns were calculated on a net basis post fee's using a number of sources that included dividend reinvestment and other significant corporate actions. In order to evaluate performance of the mutual funds within the sample, three attribution models were used, namely; pure CAPM, the Fama-French three factor model and a Carhart four factor model that included a 12 month momentum factor premium per Jegadeesh and Titman (1993).

The author alluded to the four-factor model being considered an equilibrium pricing model that encapsulates four risk premiums that are expected to explain the cross-sectional variation in

share returns. Interestingly, the author states on page 61 of the article that “I employ the model to “explain” returns, and leave the risk interpretations to the reader”. The statement was ambiguous as the explanation of returns in some sense implies that if a factor adds explanatory power by reducing pricing errors and/or lowering the level of alpha in diversified equity portfolios, then such a factor is systematic and implies some form of benefit to an investor or fund manager for having a higher loading on the factor. The higher loading in an asset pricing framework of no arbitrage implies that benefit in the form of the factor premium is offset by the “risk” inherent in the systematic factor, represented by the factor loading itself. The study found that the four-factor model was superior in explaining the variation in returns across funds. The testing of persistence in mutual fund returns first considered the formation of mutual fund portfolios using the historical 12 months of returns. Mutual funds were sorted into one of ten equally weighted portfolios and were held for the following year post sort. Portfolio sorts were conducted annually over the sample period and portfolio returns were calculated on an equally weighted basis. The sorting mechanism is highly similar to the process employed by Jegadeesh and Titman (1993), and like the results of other assets, mutual funds over the period depicted significant momentum as winner mutual funds outperformed their loser counterparts by 0.67% per month and was significant at the 5% level.

Additionally, the winner and loser portfolios were sorted into three sub-portfolios based on a 33rd /66th percentile split. The most extreme winner minus loser mutual fund portfolios achieved excess returns of over 1% per month. When using the CAPM as an attribution model, the CAPM betas failed to explain the cross-sectional variation in fund returns as both winner and loser funds exhibited high CAPM betas. However, when using the four-factor model, the spread and variation in alphas was largely explained by excessive positive and negative loadings on the size and momentum factors. The findings indicated that of the 0.67% per month spread between the winner and loser mutual fund portfolios, 31 basis points (just less than half) was explained by the momentum factor. The results of the portfolio sorts and time-series attribution indicated that the momentum factor explained a significant portion of excess returns earned by fund managers of diversified equity portfolios.

The implication of the result was more far reaching than just explaining mutual fund performance. Mutual funds are an unbiased method for testing a pricing model, specifically if there is significant cross-sectional variation in mutual fund performance and returns. The results of the study illuminated that momentum has as much, and in some cases more, explanatory power than size and value. Under the precept of no arbitrage, using the precedent set by Fama and French (1992, 1993 and 1995), Carhart (1997) effectively proved that momentum can be incorporated into a pricing model as it is persistent through time and systematic across shares. Under the pretext of no arbitrage, the study paved the way for momentum being incorporated as a systematic risk factor into equilibrium pricing models.

As described previously, Lee and Swaminathan (2000) theorized that momentum is partially explained by turnover, where turnover may be considered a crude proxy for liquidity. The dynamics of the relationship between momentum and liquidity are however more intricate as the effects of turnover were significantly different for historical winner and loser shares. A central finding of the study was that high turnover loser shares experienced longer periods of poor returns post sort and conversely, high turnover winners experienced faster reversals post portfolio formation. An implication of the findings inferred that momentum portfolios could be structured in such a way that reversal occurs significantly earlier or later past sort, all by manipulating the underlying turnover of the portfolio. The result implied a dynamic risk relationship between momentum profits and turnover, thereby indicating that turnover (or liquidity risk) provides important information pertinent to the data generating process that governs momentum returns.

Chordia and Shivakumar (2002) considered macro-economic and firm specific factors related to the business cycle in an attempt to decompose the momentum premium. In order to create a parsimonious model that predicts share returns using macro-economic factors, the studied considered factors that have been historically found to possess predictive power in terms of explaining and predicting share returns. The variables included in the study were the value-weighted dividend yield, the default spread, term spread and three month Treasury bill yield. The inclusion for each variable was based on a theoretical risk framework explaining cross-sectional variation in share returns. Dividend yield was intended to represent a proxy for unobservable components of the market risk premium as expressed by Campbell and Shiller (1987), default spread captures the effects of default premiums and the term spread was expressed as a proxy for explaining the business cycle articulated by Fama and French (1988).

The methodology employed in the study entailed using a parsimonious model which contained the lagged variables mentioned to predict the period ahead return forecast, where the factor loadings were to be estimated each month for each share considered in the study using the previous 60 months of return data. In order to test the efficiency of the model in explaining momentum returns, momentum portfolios were sorted using an identical methodology applied by Jegadeesh and Titman (1993). Momentum portfolios were sorted assuming a six-month estimation and holding period over the sample July 1926 to December 1994, using all shares listed on the NYSE and AMEX. Decile overlapping portfolios were formed and equally weighted portfolio returns were calculated over the sample period. The authors found that over the entire sample period, momentum profits were actually insignificant, producing excess returns of 0.26% per month. The authors did however note that pre-1950, momentum profits were significantly negative and when only considering the post 1950 period, momentum excess returns were 0.74% per month and significant at the 5% level.

In order to test whether momentum profits could be explained using proxies the business cycle state, the entire sample period was divided into two economic environments, namely expansionary and recessionary. In order to determine the effects of business cycle on momentum profits, simple mapping was done by measuring momentum profits over the period of expansion and recession. In each of the expansionary periods, momentum profits were statistically significant and positive while in the recessionary periods, only six of nine periods were positive and only one statistically so. The overall results were more telling as the average momentum profits across expansionary states was 0.53% per month and was significant at the 5% level. Conversely, average momentum returns in recessionary states were significantly negative achieving a negative excess return of -0.72% per month. The difference between the two states in momentum profits was 1.25% per month and significant at the 1% level. In order to determine whether the macro-economic variables that proxy for business cycle risk explain momentum profits, momentum portfolios were formed using predicted returns. Therefore, for each portfolio and component share, predicted returns were estimated monthly using the macro-economic variables described. The authors found that when using predicted returns on their momentum-sorted portfolios, the winner predicted returns were statistically and economically greater than the predicted returns of the other portfolios.

In order to determine whether actual momentum returns were explained by the predicted momentum returns, predicted momentum returns were used to reduce actual returns. Importantly, when estimating predicted returns, regressions were estimated assuming no intercept, in order to allow for the full variation to be captured the macro-economic factors considered. The reduction was applied across each share considered in the study, using rolling regressions in order to estimate forecasted one-step ahead returns. After adjusting for predicted returns, the momentum profits achieved over the sub-period July 1963 to December 1994, which originally achieved 0.74% per month in raw terms, reduced to an insignificant -1.36% per month. The results implied that momentum profits are not actually driven by historical returns in share prices but rather that the historical portion of share returns are actually predicted by the cross-sectional sensitivity of share returns to changes in business cycle proxies.

The key question that still remained was whether momentum returns were attributable to the predicted portions of the business cycle model or to the unexplained portion of returns. If momentum profits were attributable to the unexplained portion of returns, then momentum profits may be correlated with the business cycle but the business cycle does not explain momentum in terms of risk and cross-sectional variation. In order to address this, the unexplained stock specific aspects of each shares return were used to sort shares into decile portfolios, implying that momentum sorts were conducted solely on share specific returns after accounting for macro-economic (business cycle) risk i.e. the error component of the one step ahead forward

regressions. Shares were sorted into decile portfolios and were then held for six months post-sort in order to determine error based momentum portfolio returns.

The results of the sorts indicated that when sorting shares on share specific returns alone, momentum profits were positive and not significantly different from zero, only producing 0.03% per month over the July 1963 to December 1994 period. The results of the study indicated that return predictability found in momentum profits is largely attributable to the risk factor loading of momentum shares on macro-economic risk factors that proxy the business cycle. The implication of the results was that macro-economic and specifically business cycle risk explain the momentum premium.

Griffin, Ji and Martin (2003) considered risk based explanations of momentum. The study considered all previous literature that attempted to explain the momentum premium in terms of macroeconomic risks. Berk, Green and Naik (1999) produced a model that depicted firm value to be determined by interest rates, the number of current projects and the systematic risk to current projects. The model was used to explain both the value premium, long-term reversal and momentum in share prices. The model predicted that share returns will display positive autocorrelation when a firm possesses high systematic risk projects combined with low turnover in projects. In simulation analysis, the model produced both long-term reversal, value and momentum, however both the magnitude and continuation of momentum profits were different to momentum profits found on the cross-section of American shares.

Johnston (2002) developed a model that predicted the source of momentum profits to emanate from the positive relationship between share returns and internal growth rates. The equilibrium pricing model describes positive excess returns are positively related to positive shocks to dividend growth rates, resulting in positive autocorrelation in share returns, producing momentum and reversals in share returns. In simulation tests, the model successfully generated momentum returns however, reversals only seemed to occur 24 months post positive growth shock, producing momentum returns that are longer dated than those found in share returns across various markets. In order to test the above theories and the corollary macro-economic risk explanations of momentum returns, the authors considered two macro-economic risk models, the first an unconditional model per the approach of Chen, Roll and Ross (1986) and the second a conditional model per Chordia and Shivakumar (2002). The results indicated that neither the conditional model of Chordia and Shivankumar (2002) nor the unconditional model of Chen *et al.* (1986) accurately described the momentum premium across international markets providing evidence contrary to macro-economic risks explaining momentum returns.

Ahn, Conrad and Dittmar (2003) considered a stochastic discount factor as a basis for assessing the profitability of momentum strategies. The benefit of the stochastic discount factor approach is

the ability to define benchmarks for risk-adjustment that are not necessarily parametric. The reason for applying the approach emanated from the general failure of risk based explanations of momentum, as previous evidence proved that risk-adjustment resulted in risk adjusted returns being significantly greater than raw average returns. The authors attribute the poor performance of parametric risk models to the "bad model" problem discussed by Fama (1998). A stochastic discount factor is a necessary condition for market equilibrium, which is directly associated with efficiency and therefore risk. The core differentiator relates to the non-parametric nature of the estimated benchmarks derived using the GMM procedure, defining non-parametric risk benchmarks as opposed to parametric benchmarks such as those utilized by the Fama-French three factor and APT models. In order to estimate the stochastic discount factor, the assumption of no arbitrage is applied in deriving the pricing kernel. The result is that the stochastic discount rate is expected to produce a zero expectation for excess returns (in excess of the prevailing risk free rate) of all assets within an economy. In order to proxy for assets used to define the stochastic discount factor, momentum portfolios were sorted using the universe of share listed on the CRSP over the period December 1962 to December 1997. Like Jegadeesh and Titman (1993), shares were sorted into one of ten deciles based on historical performance over the previous 3, 6, 9 and 12 month periods and held for identical time frame, skipping a single month between the estimation and holding period in order to mitigate the effects of bid-ask bounce and other micro-structure issues. Portfolios were sorted monthly, therefore allowing for overlapping portfolio construction and returns were calculated on an equally weighted basis.

A further requirement of estimating the non-parametric pricing kernel is a set of basis assets that vary through time but and are simultaneously not highly correlated. Following King (1966), industry groupings were used and constructed annually based on generic industry groupings (SIC codes). In initial results, momentum was present over the period considered but seemed marginally lower than the results presented by Jegadeesh and Titman (1993). In order to test whether risk could explain momentum profits over the period, initial tests were conducted that considered a number of parametric performance measures such as the CAPM and Fama and French three factor model. Like previous studies, the authors found that after adjusting for risk using the CAPM model, 9 of the 16 strategies delivered excess returns (portfolio alphas) that were greater than their raw profits. The average excess risk-adjusted returns across the 16 strategies employed was approximately 0.7% per month and virtually identical to the raw 0.71% per month. Similarly, when using the Fama-French model, all of the 16 risk-adjusted returns were significantly greater than their raw counterparts, averaging 1.18% per month, post risk-adjustment.

When using the unconditional performance measures, estimated using the unconstrained non-parametric GMM estimations based on the 'law of one price', momentum profits declined significantly when using the non-parametric benchmark. On average, excess momentum returns post risk adjustment were 0.35% per month, thereby reducing by 51% when compared to raw

profits. Notably, even though the effect of the non-parametric benchmark was substantial, half of the strategies still achieved significant risk-adjusted returns. Moreover, the joint test for excess return alphas being zero was rejected at the 5% level, implying that the non-parametric risk adjustment does not completely explain the momentum premium. The results of the non-parametric benchmarking provided evidence in favor of a risk based explanation of momentum. Since the pricing kernel was estimated using industry benchmarks and the weak assumption of the "law of one price" (implying no arbitrage), the fact that such a benchmark explained over 50% of momentum profits implies that 50% of the momentum premium is explained by non-parametric risk.

For the purposes of robustness, following Cochrane (1997), a mimicking portfolio was constructed that perfectly tracked the stochastic discount factor. The benefit of such a portfolio relates to the estimation of betas related to the mimicking portfolio, where the mimicking portfolio takes the form of a tangency portfolio (but isn't necessarily the tangency portfolio). Betas were then estimated using the conventional CAPM market proxy and the defined stochastic discount factor tracking portfolio. The results further strengthened the evidence presented as the betas estimated using the pricing kernel tracking portfolio rose monotonically when moving from the extreme loser to the extreme winner portfolios. In contrast, consistent with prior evidence on the subject, pure CAPM betas are highly similar for winner and loser portfolios. The results therefore indicated that the failure of conventional risk-adjusted techniques in explaining momentum profits may largely lie with the fact that momentum profits do not follow parametric distributions. The result and implication is that parametric risk-adjustment produces excess risk adjusted returns that tend to exceed raw returns. Furthermore, the allowance of non-parametric risk-adjustment entails that at least 50% of the momentum premium is compensation for risk and not the manifestation of behavioral biases.

Pastor and Stambaugh (2001) investigated the effects of liquidity on the cross-sectional variability in share returns based on the premise that liquidity is a priced state variable. The sample considered covered all shares listed on the NYSE and AMEX over the period August 1962 to December 1999. The measure of liquidity developed in the study focused specifically on order flow that accompanied temporary price changes. Individual share liquidity was defined via OLS regression as the coefficient on the interaction variable based on the lagged sign of the previous days return multiplied by the lagged daily volume. The logic behind the "order flow variable" was that if a share is illiquid, one would expect that lagged recent returns experience a partial reversal in the immediate future. Intuitively, the more negative the coefficient value in terms of magnitude and significance, the greater illiquidity associated with the share. In order to derive a market wide liquidity measure, the coefficients for each share over the sample period were estimated and averaged on an equally weighted basis. The authors found that over the sample period, the mean liquidity measure was -0.03, implying a 3% cost for each trade in terms of liquidity.

In order to determine whether liquidity risk was priced on cross-section of shares considered in the study, liquidity based portfolios were sorted over the sample period using pre-ranking liquidity betas. Importantly, liquidity betas were defined using a multivariate time-series regression that also considered the Fama-French factors in order to remove the possibility of liquidity risk being clouded by loading on value or size. Liquidity betas were estimated using time-series regressions and shares were then grouped into decile portfolios and held for the following 12 month period. Portfolio returns were calculated on an equally weighted basis. The excess returns on each of the portfolios were then regressed on common return based factors in order to determine the return premiums and the significance of alpha. The authors found that all risk based specifications failed to explain the excess return achieved by liquidity sorted portfolios. The CAPM alpha of the low minus high liquidity portfolio was 6.4% per year, the Fama-French alpha was 9.23% per year while the Carhart alpha was 7.48% per year (all alphas were significant at the 5% level). For further robustness, the GRS tests statistic was applied in order to test whether alphas for each portfolio were jointly equal to zero. Using the three attribution models considered, the GRS statistic rejected the null at a 1% level over the entire sample period.

The attribution analysis indicated that liquidity is a priced risk factor that is not explained by size, value or momentum. In order to determine the effects on an ex-post efficient frontier, ex-post factor weightings were determined using a value-weighted and equally weighted liquidity return series as well as excess returns on size, value and momentum. The weightings in the tangency portfolio significantly favored the liquidity portfolios but largely at the expense of momentum, where the addition of liquidity dropping the momentum weighting from 20.9% to 6.5%. The results indicated that liquidity seems to supersede the excess return contribution of momentum in the ex-ante efficient tangency portfolio indicating that liquidity, as defined in the study, may explain a portion of the momentum premium.

The final test calculated alphas achieved by the momentum portfolio used in the study using Fama-French factors augmented with an equally weighted and a value-weighted liquidity variable. Over the entire sample period, the momentum alpha was 16.3% per annum when using the Fama-French factors, however, when including an equally weighted liquidity factor, the alpha dropped to 8.41% per annum and was only significant at the 10% level. The evidence therefore provided proof in favor of liquidity being a market wide proxy and more importantly, that liquidity, as defined in the study, explained almost half of the momentum premium achieved over the period.

As referenced previously, Cooper, Gutierrez and Hameed (2004) conducted a study that attempted to link long-term reversal and momentum to market states. The focus now relates to the risk-return aspect of the study as opposed to the mere identification of momentum on the cross-section of US shares over the period January 1926 to December 1995. The authors considered the behavioral explanations of momentum and long-term reversal and momentum

provided by Daniel, Hishleifer and Subrahmanyam (1998) and Hong and Stein (1998) where the former considered “self-attribution bias” as a driver of momentum and reversal while the latter developed a theory based on “news watchers” and “momentum traders”. Both theories create allowances for momentum to be higher in positive market states as opposed to negative market states, and further that positive market states will further lead to greater level of reversal in momentum profits. However, the authors shift from the support of behavioral theories to those consistent with Chordia and Shivankumar (2002), as by implication, evidence in favor of momentum profits being highly sensitive to market states implies that there is certainly a significant risk element driving momentum returns. In order to test the effects of the market status on portfolio returns, the ‘market state’ was defined at each formation period using the historical three year return of the CRSP value weighted market index.

When dividing the momentum portfolios into two further portfolios based on the market state, momentum profits and reversal seemed highly sensitive to market conditions measured over the previous 36 months. The results of the study were in fact two-fold as there was support for both behavioral and risk based explanations of momentum. Consistent with behavioral theories, momentum profits are expected to be greater in positive market states, as such states pre-empt the highest levels of self-attribution bias and information asymmetry, thereby pushing momentum profits higher. Similarly, the markets effect on momentum profits is directly linked to market risk explaining momentum but not in a linear (parametric) setting. However, the evidence presented also proved somewhat difficult to rationalize from a risk or behavioral framework. Considering behavioral theories of momentum, momentum in market UP states is expected to experience greater levels of reversal, while the contrary was found. Similarly, the authors tested whether market states were related to variation in macro-economic risk per Chordia and Shivakumar (2002). The findings indicated that the market state seems independent of the variation in economic factors, thereby disproving the notion that momentum is compensation for macro-economic risk.

Sadka (2006) extended the study of the relationship between liquidity risk and price and earnings momentum. The author presented an argument similar to the ‘limits to arbitrage’ hypothesis of Pontiff (2006) and Lesmond, Schill and Zhou (2004) where evidence dictates that momentum is highly sensitive to transaction and holding costs. From this, a corollary emerged where momentum profits may be related to the variation in liquidity risk, where liquidity risk is related to both arbitrage related holding and transaction costs. The focus of liquidity in the study shifts from the conventional firm-level liquidity to a market wide liquidity factor that possibly explains the systematic variation in momentum profits. Liquidity was first defined as the price impact induced by trades and then separated into variable and fixed effects. Permanent or fixed effects were assumed to be attributable to insiders or informed traders trading on private information while transitory effects were associated with market making trades.

The sample used in the study covered a combination of high and low frequency data sets over the period January 1983 to August 2001 and was limited to the cross-section of shares listed on the NYSE. The permanent and variable liquidity measures were calculated for each share over the sample period. In order to determine the effects of liquidity on price and earnings momentum, the singular liquidity measures were cross-sectionally cumulated on an equally-weighted basis in order to define market wide fixed and variable liquidity proxies that varied through time. In order to test the effects of the market wide liquidity factors on momentum profits, two sets of 25 portfolios were sorted on price and earnings momentum respectively. Price momentum portfolios were sorted assuming an estimation and holding period of 12 months. Portfolio returns were calculated on an overlapping, equally weighted basis, allowing for a one-month gap between estimation and investment. In order to form portfolios based on earnings momentum, shares were sorted on standardized unexpected earnings. In price momentum sorts, prior winners achieved monthly returns of 1.44% per month and the momentum premium was 1.93% and significant at the 1% level. Similarly, the earnings momentum results exhibited positive yet economically lower momentum as the high minus low earnings surprise premium was 0.69% per month and significant at the 5% levels.

In order to determine the cross-sectional effects of liquidity on asset prices, the two sets of 25 price and earnings momentum portfolios were analyzed using Fama-Macbeth cross-sectional regressions. Several explanatory factors were used including the value-weighted market proxy, Fama and French (1992) value and size proxies and the fixed and transitory market liquidity measures. The cross-sectional results indicated that transitory market liquidity failed to display any pattern and explain any variation in portfolio returns. Conversely, the factor loadings on the fixed market liquidity factor were statistically significant, where historical loser shares maintained negative factor loadings while historical winner shares maintained significantly positive factor loadings.

The results further indicated that 0.54% and 0.57% of price and earnings momentum average monthly returns was explained by ‘fixed’ market wide liquidity Robustness tests were conducted using bivariate sorts on momentum (price and earnings) and market wide fixed effects liquidity. The results of the bivariate sorts further confirmed the effect of liquidity on momentum profits as excess momentum profits increased monotonically as portfolios moved from low to high liquidity where excess price momentum returns increased from 0.89% to 1.25% while excess earnings momentum returns increased from 0.5% to 1.07%. The results of the study were consistent with those of Pastor and Stambaugh (2001) as the results provided evidence in favor of a liquidity based explanation of momentum, implying that a portion of momentum profits (both price and earnings momentum) is compensation for liquidity risk.

Chordia and Shivankumar (2006) examined the relationship between earnings momentum and price momentum. The authors found that earnings momentum is a systematic variable that is cross-sectionally priced and that price momentum is merely a manifestation of earnings momentum, but since earnings momentum is not risk based, excess returns achieved through price momentum cannot be considered compensation for risk. Sagi and Seasholes (2007) examined the relationship between momentum profits and firm specific attributes and whether such can be used to augment the profitability of momentum strategies. The study found that momentum in share returns and specifically autocorrelation in share returns that induces momentum is highly sensitive to firm specific attributes, implying that firm specific attributes that contribute to firm specific, non-diversifiable risk explain the momentum anomaly. The result is contrary to the assertions made in behavioral finance studies and is consistent with the likes of Conrad and Kaul (1998), indicating that risk and not market psychology drives momentum profits.

Liu, Warner and Zhang (2008) investigated the ability of macroeconomic risk explaining the momentum premium. The study centered on industrial production growth, motivated largely by Chen, Roll and Ross (1986) and more specifically Johnson (2002). Johnson (2002) developed a theoretical risk-based explanation of momentum that attributed momentum to cross-sectional variation in firm growth rates and that share returns can be expected to produce higher degrees of autocorrelation when growth rates are extremely high or low. The authors therefore hypothesized that if industrial production growth (GDP growth) is a proxy for expected growth, firms with larger factor loadings should display higher growth and positive returns coupled with positive autocorrelation and thereby momentum. In order to determine whether industrial production growth is priced, the study considered all shares listed on the AMEX, NASDAQ and NYSE over the period January 1960 to December 2004. Momentum portfolios were sorted per Jegadeesh and Titman (1993), using the common six month estimation and holding period, allowing for a single month gap between estimation and investing in order to remove potential biases due to bid-ask bounce and micro-structure effects. Portfolio returns were calculated on an equally weighted basis and portfolio formations occurred monthly, implying overlapping portfolio returns converging on a single return series. The authors found that excess momentum returns over the sample period were 0.77% per month and significant at the 5% level.

Consistent with prior literature, the authors found that conventional risk proxies fail to explain the momentum premium. Using both the CAPM and Fama-French three factor model, momentum alphas were 0.81% and 0.96% per month respectively and both were significant at the 5% level. Following Chen, Roll and Ross (1986), macro-economic variables were included in the analysis with each macroeconomic variable was led by a single month. When using industrial production growth as a single factor, the factor weighting achieved on the loser portfolio was 0.04 while factor loading for the winner portfolio was approximately 14 times larger. The results were further strengthened by the winner factor loading being statistically greater than the loser factor loading,

albeit at the 10% level. The relationship was by no means monotonic as the loading difference was largely driven by the top four deciles factor loadings. Importantly, the factor loading in the highest momentum decile was greater than the combined factor loading of the bottom nine portfolios and the difference was significant at the 1% level. In addition, when controlling for size and value, industrial production growth factor loadings were largely unchanged, however the spread between the extreme winner and loser shares in terms of factor loadings actually increased. Lastly, the inclusion of the other Chen, Roll and Ross (1986) factors also failed to detract from the asymmetric pattern in factor loadings across momentum portfolios, with high momentum portfolios displaying significantly larger factor loadings than there lower decile counterparts.

In order to determine how factor loadings evolve month-by-month, event time factor regressions were performed for each month after portfolio formation. Portfolio returns were then pooled cross-sectionally and pooled time-series factor loadings were estimated for each portfolio resulting in a 12 month event time factor loading series, which presented as cross-sectional factor loading averages. The findings indicated that factor loadings display the highest level of cross-sectional asymmetry one month post portfolio sorts where loser portfolios achieved factor loadings of -0.17 compared to winner portfolio loadings of 0.63. Over the next three months post sort, the loser portfolio experience significant increases in the industrial production factor loading, increasing to -0.05. The increase in factor loadings for the winner portfolio was more modest in comparison increasing to 0.71. In the following months, the loser portfolios continued to experience significant increases in factor loadings while winner portfolios experienced simultaneous significant decreases, resulting in factor loadings converging at 0.35 over the 12 months post sort.

The final set of tests intended to determine the percentage of momentum profits explained by the growth in industrial production. Fama-Macbeth regressions were run in order to determine the risk premium attached to the growth in GDP macro-economic factor. In the two-pass regression analysis, time-series factor loadings were measured using two methods, namely the 60 month rolling window and expanding window methodology. The expanding window methodology allows for the increasing data window used to estimate time-series factor loadings, creating window that captures all historical data points prior to the date of the first-pass regression. The authors found that the risk-premium was highly sensitive to the first-pass methodology applied were rolling window time-series estimations produced a factor premium of 0.33% (significant at the 5% level) compared to the extending window methodology which produced a risk premium of 1.16% per month which was significant at the 1% level. In order to determine the percentage of momentum profits explained by growth in GDP production, the methodology of Griffin, Ji and Martin (2003) was applied where momentum returns were estimated using a Fama-French model augmented with the GDP production growth factor. The simulated returns were then compared to actual returns in a form of a ratio, depicting the percentage of momentum profits explained by the

‘improved’ pricing model. The findings indicated that the inclusion of the GDP growth factor explained 66% of the momentum premium at best. The authors concluded that the growth model of Johnston (2002) seems to contain merit as GDP production seems to explain the cross-sectional difference in momentum portfolios, even though the factor is only able to explain, at most, two thirds of the momentum premium over the sample period.

As referenced in section 2.2.2, Asness, Markowitz and Pedersen (2013) explored momentum and value strategies across singular equities, market indices, currencies, bonds and commodity futures. Momentum and value portfolios were formed across and sorted into terciles over eight asset classes, resulting in 48 test portfolios. Further, value and momentum factors were constructed individually for each asset class using weighting methodology based on rank, scaled by the number of securities considered as well as scaling factor. The authors found that irrespective of the asset class, value and momentum were present, significant and consistently negatively correlated throughout the various asset classes over the sample period. More importantly, the findings of the study produced evidence in favor of a global momentum premium, which implies that the profit garnered via momentum strategies is a systematic phenomenon. The inclusion of a factor premium within a pricing model requires a ‘universal’ premium present on the cross-section of various assets classes, whereas many prior asset pricing tests include factors that are found solely on the cross-section of the specific asset class (normally equity) in the geographic market considered.

Asness *et al.* (2013) produced evidence that momentum not only applies across international equities, but is also present across non-equity assets, implying a cross-asset factor that explains the cross-sectional variation in all financial asset returns. Core to the explanatory power of the global momentum premium, the authors created a global three factor model that was applied against momentum and value portfolios across the eight asset classes considered, size, value and momentum portfolios sorted using the cross-section of US shares and the cross-section of 13 hedge fund indices. The results of the analysis indicated that global momentum and value factors explained a major proportion of the various asset returns and were far more effective than the conventional equity only Fama and French (1992) and Carhart (1997) attribution models. The results showed that the lack of a plausible driver behind momentum profits does not detract from the evidence of momentum being a globally priced phenomenon that drives variations in asset returns.

2.4 CHAPTER SUMMARY

The literature presented describes the plethora of evidence in favor of momentum being present across multiple geographical markets and asset classes. The presence and consistency of momentum is undeniable, yet there is still no single unifying theory that explains the persistence

of momentum in share prices over the short to medium term. There are, however, two distinct schools of thought that have emerged that attempt to describe the momentum premium. The 'risk' based explanations of momentum extend beyond conventional risk based explanations applied in literature, specifically those tested via time-series attribution regressions where other noted risk premiums are applied as state factors. A number of studies have shown that application of such a methodology (for instance the usage of a Fama-French three factor model) fail to explain the momentum premium, and more often than not actually result in momentum premiums being greater than their non-risk adjusted counterparts.

A number of the unique 'risk' based explanations of momentum deserve mention. Conrad and Kaul (1998) hypothesized that the momentum premium is solely attributable to investing in high mean return shares and simultaneously shorting low mean returns shares. The implication of the model is therefore that the level of cross-sectional diffusion in mean returns lead to greater momentum profits thereby precluding the possibility of the momentum premium being driven by behavioral biases. The source of cross-sectional diffusion in mean returns can easily be reconciled with risk-based theories of asset pricing as mean returns are anticipated to vary with underlying state factors (risks) that are expected to drive shares returns. A distinctive flaw of both the findings and the assumed model applied relates to the assumption and requirement of mean stationarity, which is impossible given that momentum profits are found to reverse assuming holding periods in excess of a year. Johnson (2002) and Sagi and Seasholes (2007) applied theoretical firm specific attribute models that rely on current growth prospects (options) that drive positive autocorrelation in returns and therefore result in momentum. Both studies found via simulation analysis that momentum is present when firm specific attributes such as growth options are assumed.

The second and more generally accepted driver of the momentum premium is market psychology or behavioral finance. Importantly, the discovery of momentum and long-term reversal in share prices and failure of single risk-based explanations of momentum resulted in the establishment of behavioral finance, where psychological phenomena are applied in order to reconcile winner shares first experiencing return continuation over short to medium investment horizons and then reversing over the longer term. Three of the most noteworthy behavioral explanations of the momentum premium are attributable to Barberis *et al.* (1998), Daniel *et al.* (1998) and Hong and Stein (1999). The theories applied all differ based on the specific psychological biases and underlying theoretical frameworks, yet are uniform in the acceptance that behavioral biases create upward buying pressure in historically positive performing shares, resulting in momentum. Similarly, the upward pressure tends to extend profits to points beyond the intrinsic value of the underlying asset, forcing a correction over the longer term. In simulation analysis, all of the studies found patterns consistent with the momentum premium and the eventual reversal of momentum profits over periods in excess of twelve months.

Risk based explanations of investment anomalies imply that an underlying risk drives the resulting expected return, however, there is no rational risk that explains why momentum, i.e. betting on historical positive performance, is riskier than applying a contrarian strategy (which is much easier to rationalize from a risk-based perspective). Behavioral theories that govern asset prices benefit from the fact that risk based explanations are bounded by rationality. The notion of irrationality (and potentially non-linearity) describing the cross-sectional variation in share prices allows for the explanation of momentum through underreaction, reversal through overreaction and at the extreme, the occurrence of market bubbles. A key issue with behavioral finance is that it is not necessarily testable, but rather is an alternative hypothesis (H_A) to the null of risk explaining the momentum premium. Empirically testing whether momentum does eventually reverse and is not driven by other priced anomalies (or risk factors) leads to the rejection of momentum not being compensation for some unknown risk. The natural alternative could be that momentum is not driven by risk and rather by behavioral biases, yet such conclusions would not preclude that momentum is driven by some unknown risk that is yet to be considered, similar to the like of principal component analysis. Additionally, even though all of the behavioral studies found (through simulation analysis) that their models produced both momentum and reversal, all achieved returns that were significantly lower than those described in the literature. Therefore, to acquiesce and accept that momentum is solely driven by behavioral biases would be both myopic and premature at best.

The source of momentum profits is highly topical and there is evidence both in favor of ‘risk’ and ‘behavioral’ explanations. Moving away from the source of the momentum premium, there is no dispute related to the existence and persistence of momentum in developed markets, barring that of Japan and other Asian economies. Emerging market evidence of momentum is somewhat mixed, with a number of studies finding a significant emerging market momentum premium, while others the complete opposite. The base market to be analyzed in this study is the JSE, a prominent emerging market with the most developed economy and stock exchange in Africa. The outcomes of the evidence to be presented provides key information in terms of the momentum premium in largely developed emerging markets. The analysis of the literature presented above points to a distinctive gap in both the South African and emerging market literature in terms of the momentum premium. The majority of local (South African) financial economic literature relates to general tests of the CAPM or market beta, size and value and to a far lesser extent momentum. Significant credit can be extended to the likes of van Rensburg (2001), van Rensburg and Robertson (2003), Basiewicz and Auret (2009), Gilbert, Strugnell and Kruger (2011) for producing base literature that attacks the EMH and the applicability of the CAPM to the JSE. Unfortunately, the rigor that has been applied to testing beta, value and size has yet to be extended to momentum.

In comparison, the tests of momentum on the JSE have been limited to relatively simplistic tests assuming univariate and (at most) bivariate frameworks. Specifically, on a univariate basis, the current body of literature fails to consider methodological implications such as the effects of indirect and direct costs on momentum profits, the effects of liquidity and price impact, whether micro-structure effects negatively bias momentum profits and lastly, the effects of market capitalization and equal weighting. Such information is key to understanding the momentum premium on the JSE and whether it conforms to the momentum premium found in developed markets. Such information is central to understanding the nuances of momentum on the JSE, its' sensitivities to trading costs, short-term reversal and the effects of portfolio constituent weightings. Therefore, by providing and describing such findings, this study intends to significantly add to current body of literature related to univariate momentum and the effects of methodological intricacies on momentum profits.

On a bivariate basis, there is limited literature that considers the independence of momentum and interaction with other stylistic anomalies. To the best of the authors knowledge, bivariate tests have been limited to value proxied by price-to-book, liquidity proxied by the turnover ratio and lastly, idiosyncratic risk. There are a number of internationally recognized pricing anomalies that have not been considered, presenting a further significant gap in the current body of South African literature. This study intends to consider six pricing anomalies. The application of bivariate tests across numerous pricing anomalies allows for the determination of both the singular independence of momentum (confined to two variables) as well as the interaction between momentum and the said pricing anomalies. The information and findings will further significantly augment the literature on momentum, extend the literature on the already considered factors and fill the major gaps in the literature that relate to anomalies that have yet to be considered in a South African framework. Furthermore, bivariate sorts are in effect a simplistic test of independence, causality and correlation. The null of momentum being independent of other non-momentum factor anomalies is a bivariate risk-based test of momentum. If it is found that the momentum premium is significantly reduced through dual sorting on other non-momentum factors, one can conclude that the momentum premium on the JSE is compensation for the non-momentum factor risk.

More importantly, the current body of South African literature has failed to transcend bivariate tests and progress to multivariate tests of momentum, which in turn would represent the determination of whether momentum is an independent factor i.e. whether noted pricing anomalies or risk factors drive momentum profits on the JSE. A multivariate setting that utilizes factor premiums through time-series attribution regressions allows for the determination of whether a combination of non-momentum factor premiums reduce the time-series alphas of momentum portfolios. The obvious benefit of multivariate tests over bivariate sorts is that multivariate regression allows for a more stringent risk-adjustment of returns through

contemporaneously combining non-momentum factors in a single test, determining which non-momentum factors significantly contribute to the momentum premium and lastly, whether the momentum premium is significant post risk-adjustment. The results of such tests would significantly contribute to the current body of South African literature and meaningfully augment the current evidence related to the momentum premium on the JSE.

Lastly, and most importantly, the identification of momentum on the JSE should naturally lead to tests that attempt to determine whether momentum is in fact a priced factor. Unfortunately, to date (and to the best of the authors knowledge), there virtually no evidence presented in the South African literature that tests whether momentum is a priced factor on the JSE, implying that momentum in share prices actually contributes to the cross-sectional variation in share returns on the JSE. The testing to be conducted will assume that momentum takes the form of an explanatory variable as opposed to a dependent variable, where momentum will be compared to the non-momentum factor premiums considered across this study. Extending the work of Basiewicz and Auret (2010), cross-sectional regressions are to be applied in order to define whether momentum (as well as the other noted non-momentum factors) explain the cross-sectional variation in share returns listed on the JSE. Such evidence will significantly to the current body of South African literature related to momentum, asset pricing and risk allocation applicable to both academia and investment practitioners alike.

Following the methodologies described in the literature, momentum will be tested on a univariate, bivariate and multivariate basis. The tests that follow are empirical and therefore are more consistent with risk based tests of momentum, however, in univariate tests momentum portfolios will be tested to determine whether return patterns on the cross-section of shares listed on the JSE conform to international literature and behavioral theories i.e. producing both short and medium-term momentum and long-term reversal. The central research question of this study deviates from attempting to determine what drives momentum on the JSE. The focus turns to whether momentum is independent on the cross-section of shares listed on the JSE and most importantly, whether momentum drives the cross-sectional dispersion in share returns. The central theme therefore distances itself from defining whether momentum profits are attributable to underlying risks or systematic behavioral biases, but rather attempts to define whether momentum is an empirically defined **priced factor**. Following a methodology similar to that of Chen, Roll and Ross (1986) and Fama and French (1992), if momentum is positive, persistent and priced, it deserves incorporation within a factor pricing model, irrespective of whether a suitable risk based explanation is available. The sections that follow are in many instances unique to the South African literature on the subject of momentum and asset pricing and continuously make reference to prior International and local literature that is pertinent to the empirical nature of tests conducted.

CHAPTER THREE: UNIVARIATE TESTS OF MOMENTUM ON THE JSE

The following chapter intends to test whether medium-term price momentum is present on the cross-section of shares listed JSE. Using the methodology of Jegadeesh and Titman (1993, 2001), shares are sorted applying four estimation periods (*E* = 3, 6, 9 and 12 months) and held for four portfolio holding periods (*H* = 3, 6, 9 and 12 months) post sort[4]. The portfolio 'optimization' methodology employed in this study provides additional insight when compared to previous tests conducted in South African literature (Fraser and Page, 2000, van Rensburg, 2001, Muller and Ward, 2013) as further robustness tests are applied in order to determine the pervasiveness and sensitivity of momentum to variations in sorting methodology, liquidity and trading costs. The test portfolio simulations are designed to consider the effects of transaction costs (proxied by price as per Basiewicz and Auret (2009)), liquidity (proxied by a combination of historical zero daily trades and turnover per Liu (2006) and Pastor and Stambaugh (2003)), the effects of value and equally weighting returns and lastly, whether bid/ask bounce and micro-structure effects affect momentum profits. As mentioned previously, the dataset employed in this study forms part of the Findata@Wits database that contains historical share data across the entire cross-section of shares listed over the time period December 1989 to June 2015. The time-period analyzed is limited to start in January 1992, as accurate zero daily trade data is only available from September 1991 onwards.

3.1. METHODOLOGY AND RESEARCH DESIGN

The Methodology and research is design is described in the subsections 3.2-3.4 that follow.

3.2. SORTING MECHANISM

The portfolio sorting procedure applied in this study is virtually identical to that of Jegadeesh and Titman (1993, 2001) as shares are sorted into one of five quintile portfolios at each sort date based on their historical cumulative return over the previous *E* and *E-1* periods, where portfolio one represents the extreme historical winner portfolio (i.e. shares that have achieved the highest historical cumulative returns) and portfolio five represents extreme historical losers. The sorting methodology can be expressed mathematically by equations 3.1 and 3.2.

$$Momentum_i = \sum_{t*=0}^{E} R_{i,t-t*} \qquad (3.1)$$

[4] Jegadeesh and Titman (1993, 2001) applied *J* and *K* as variables when referring to estimation and holding periods

$$Momentum_i = \sum_{t*=0}^{E} R_{i,t-t*-1} \qquad (3.2)$$

The formulas indicate that the cross-sectionally defined time-series momentum for share *i* is based on the estimation period *E* which takes the values of the historical 3, 6, 9 and 12 months prior to the portfolio sorting date. Equation 3.1 represents the cumulative historical return estimation without an allowance for a one month gap between portfolio estimation and holding (investment) while equation 3.2 applies the methodology of Asness (1997), allowing for a one month gap by excluding the most recent month of the estimation period *E* (therefore *E-1*). At each formation date, shares are required to have at least *E* months of historical returns in order to be eligible for inclusion.

Further restrictions are applied in order to determine the effects of transaction costs proxied by price and liquidity proxied by a combination of the number of historical zero daily trades and average turnover over the previous year (see Lesmond, Schill and Zhou (2004), Korajczyk and Sadka (2004) van Rensburg (2001), Basiewicz and Auret (2009), Hodnett, Hsieh and van Rensburg (2012)) . At each portfolio formation date shares are first ranked on their historical cumulative returns (per equations 3.1 and 3.2) and simultaneously subjected to exclusion filters based on their last traded closing price as well as their combined rank based on turnover and number of zero daily trades over the previous trading year. The price filter is applied and excludes shares based on three price levels, namely; 0, 50 and 100 cents. Similarly, the liquidity filter is a combination of historical zero daily trades and average turnover ratio, where turnover is proxied by trading volume scaled by number of shares in issue. The maximum number of zero daily trades is set at 200, 150 and 100 and is combined with a turnover filter where shares are excluded if they fall within the bottom 1st, 5th and 10th percentile of cross-sectional historical average turnover. The benefit of the price and liquidity filters allows for the determination of momentum dynamics when constraining the investable universe to account for transaction costs and liquidity as per Basiewicz and Auret (2009).

The purpose of the application of simultaneous price and liquidity filters is twofold. Firstly, as described in the literature review, a number of studies have found that a large proportion of the momentum premium is attributable to the short position of the long-short winner minus loser strategy. In order to add realism to the paper returns produced by the simulated test portfolios, positions are constrained to account for transaction costs and liquidity effects. The sensitivity of momentum profits to variations in both exclusion criteria will provide important evidence related to the realistic profits and “tradability” of momentum on the JSE. Secondly, the sensitivity of momentum to transaction costs and liquidity constraints may provide evidence related to the ‘limits to arbitrage’ hypothesis per Pontiff (2006), specifically the direct and indirect costs involved in executing to momentum strategies.

3.3. PORTFOLIO RETURNS

Portfolio returns are calculated on an arithmetic buy-and-hold basis assuming both equal and value (market capitalization) weighting. At portfolio formation, shares are assigned an initial weighting based on the weighting schematic applied. In the case of equal weighting, each share is assigned an equivalent weight based on the number of shares within the portfolio. This implies that in a portfolio of *n* shares, each share receives an initial weighting of *1/n*. Under the assumption of value weighting, shares receive a relative weighting at portfolio formation based on their latest (*t-1*) natural logarithm of market capitalization. Importantly, the weight of each constituent share is allowed to vary across the portfolio holding period (*H*) and weights are only reassigned at the next portfolio sort. Portfolio returns are expressed mathematically based on equations 3.3 and 3.4 below.

$$PF_t = \sum_{i=1}^{n} \sum_{t=1}^{H} W_{i,t-1}(1 + r_{i,t}) \qquad (3.3)$$

$$PFR_t = \frac{PF_t}{PF_{t-1}} - 1 \qquad (3.4)$$

Where PF_t represents the respective test portfolio (portfolios one (winner) to five (loser) based on historical cumulative average return) at time period *t* and is equal to the sum of weights of each constituent share *i* grown using the total return for the respective share (r_{it}) over the next *H* periods. W_{it} represents the constituent shares weight and PFR_i represents the arithmetic one-period return of the test portfolio at time *t.* Generally, most momentum studies assume equal weighting in calculating portfolio returns (Jegadeesh and Titman (1993, 2001), Rouwenhorst (1998)). The addition of value weighting strengthens the power of the test as it will determine the relationship between momentum profits and the assumed portfolio weighting methodology. Portfolio returns are calculated on a rolling window basis, assuming that two portfolio initiation dates, one that starts in January 1992 and the other in June 1992.

This implies that the final time-series of portfolio returns is a convergence of two simulated momentum portfolios that are insensitive to beginning and end of sample bias. Lastly, if a share delists within the portfolio holding period *H*, the share is assigned a -100% penalty return. Considering all the permutations, a total number of 288 test portfolios are formed assuming varying holding periods, estimation periods, price filters, liquidity filters, equal weighting, value weighting and the assumption of no gap and a one month gap between portfolio estimation and investment (4 x 4 x 3 x 3 x 2 = 288). For the purposes of tractability, all momentum results are depicted as the excess returns of winner portfolios (portfolio one) over their extreme loser counterparts (portfolio five) over the sample period. Lastly, for ease of reference, portfolio

estimation and holding periods are described using their monthly (numerical) window period values separated by a semi-colon. For example, the 12;3 portfolio refers to the excess momentum return achieved by the portfolios assuming a twelve month estimation period and three month holding period.

3.4. PORTFOLIO RESULTS

The portfolio results that follow depict the excess returns (Winner minus Loser or "WML") for each of the assumed estimation and holding periods, price and liquidity filters, equal and value weighting schematics and allowance and non-allowance for single month gap between portfolio estimation and holding period. Excess returns are described as percentages and are accompanied by p-values associated with two-tailed paired sample t-test for each portfolio simulation.

3.4.1 Excess momentum profits assuming equal weighting and no gap between estimation and holding period

The results of the momentum test portfolios simulated assuming equal weighting and no gap between portfolio estimation and holding period are presented in Table 3.1 that follows. The portfolio estimation period (*E*) and holding period (*H*) are presented in the left column and upper row of the table. With each test portfolio, *PF* relates to the price filter where *PF1* represents the least stringent price filter (0 cents) and *PF3* represents the most stringent (100 cents). Similarly, *LF* relates to the liquidity filter applied where *LF1* represents the least stringent liquidity filter (200 maximum zero daily trades and average turnover in the bottom 1st percentile) while *LF3* represents the most stringent (100 maximum zero daily trades and turnover in the bottom 10th percentile).

In order to derive a high level view of momentum returns assuming equal weighting and no gap between portfolio estimation and holding period, the summarized holding period excess returns are presented in Figure 3.1. Consistent with international and local literature, irrespective of estimation and holding period, all excess momentum returns are positive. Further, there is significant variation in momentum profits based on the assumed portfolio estimation and holding period.

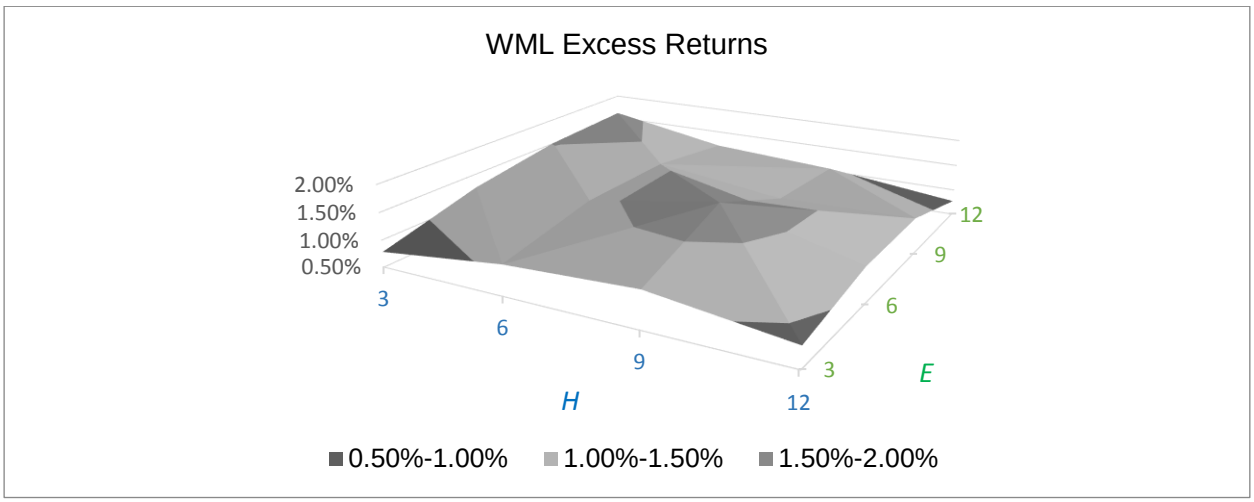


Figure 3.1: Excess momentum returns assuming equal weighting and no gap between estimation and holding period where E and H represent portfolio holding and estimation periods.

Figure 3.1 above depicts the excess returns based on variations of portfolio estimation and holding periods. The highest excess returns seem to be present in two regions, namely the estimation and holding periods between six and nine months (6;6 and 6;9) as well as the 12;3 momentum portfolio. Moreover, when the estimation period is below six months (Axis E), excess returns increase monotonically as the holding period increases between three and nine months but decreases as the holding period increases beyond 12 months. At an estimation window between nine and 12 months, returns decrease monotonically given an increase in the assumed portfolio holding period. When allowing for a variation in the estimation period, each portfolio holding period experiences an increase in average excess returns between the estimation periods of months three and nine and decreases thereafter, barring the three month holding period where excess returns maintain a positive relationship with the estimation period. The high level mapped view provided by Figure 3.1 indicates that momentum profits are present on the cross-section of shares listed on the JSE and excess returns are positive irrespective of estimation or holding period. In order to identify the dynamics of momentum and its sensitivity to liquidity and transaction costs, the results presented in Table 3.1 are to be explored.

Considering the results presented in Table 3.1, an interesting pattern emerges when allowing for variations in price and liquidity within the test portfolios. Firstly, the introduction of liquidity and price filters results in significant variation in excess returns across the various estimation and holding period test portfolios (see figure 3.2 below). Considering the effects of the liquidity on momentum excess returns, at portfolio holding periods between three and six months, momentum profits maintain a weakly positive relationship with liquidity, where the relaxing of the liquidity filter results in a lower average excess returns.

	H	3			6			9			12		
E		**PF1**	**PF2**	**PF3**	**PF1**	**PF2**	**PF3**	**PF1**	**PF2**	**PF3**	**PF1**	**PF2**	**PF3**
3	**LF3**	1.043%	0.953%	0.867%	1.275%	1.090%	0.930%	1.039%	1.054%	1.194%	0.821%	0.639%	0.626%
		0.084	*0.109*	*0.145*	***0.033***	***0.067***	*0.109*	***0.082***	***0.075***	***0.038***	*0.173*	*0.277*	*0.276*
	LF2	0.739%	0.899%	0.755%	1.271%	1.153%	0.967%	1.363%	1.240%	1.182%	1.128%	0.890%	0.854%
		0.194	*0.107*	*0.179*	***0.027***	***0.040***	***0.083***	***0.018***	***0.024***	***0.030***	***0.058***	*0.102*	*0.116*
	LF1	0.367%	0.781%	0.650%	1.008%	1.013%	0.858%	1.202%	1.176%	1.127%	1.090%	0.955%	0.899%
		0.497	*0.155*	*0.220*	***0.060***	***0.051***	***0.101***	***0.025***	***0.024***	***0.029***	***0.052***	***0.062***	***0.082***
6	**LF3**	1.447%	1.400%	1.204%	1.321%	1.428%	1.273%	1.854%	1.830%	1.657%	0.947%	0.990%	1.102%
		0.016	***0.018***	***0.041***	***0.023***	***0.014***	***0.027***	***0.001***	***0.001***	***0.004***	***0.097***	***0.074***	***0.052***
	LF2	1.334%	1.393%	1.169%	1.412%	1.602%	1.424%	1.927%	1.919%	1.642%	1.133%	1.212%	1.208%
		0.017	***0.011***	***0.032***	***0.011***	***0.003***	***0.008***	***0.000***	***0.000***	***0.002***	***0.039***	***0.021***	***0.023***
	LF1	0.934%	1.254%	1.024%	1.202%	1.576%	1.400%	1.836%	1.844%	1.645%	1.274%	1.332%	1.331%
		0.079	***0.016***	***0.048***	***0.022***	***0.002***	***0.006***	***0.000***	***0.000***	***0.001***	***0.017***	***0.008***	***0.008***
9	**LF3**	1.727%	1.619%	1.535%	1.351%	1.210%	1.266%	1.241%	0.895%	1.044%	1.012%	0.793%	0.995%
		0.004	***0.006***	***0.009***	***0.023***	***0.040***	***0.030***	***0.034***	*0.125*	***0.068***	***0.089***	*0.181*	***0.092***
	LF2	1.557%	1.582%	1.454%	1.529%	1.521%	1.449%	1.268%	1.142%	1.210%	1.526%	1.203%	1.248%
		0.006	***0.004***	***0.008***	***0.007***	***0.006***	***0.008***	***0.023***	***0.034***	***0.024***	***0.009***	***0.029***	***0.024***
	LF1	1.283%	1.468%	1.326%	1.511%	1.546%	1.461%	1.135%	1.111%	1.141%	1.494%	1.227%	1.190%
		0.017	***0.004***	***0.010***	***0.005***	***0.003***	***0.004***	***0.033***	***0.028***	***0.023***	***0.007***	***0.017***	***0.022***
12	**LF3**	1.644%	1.592%	1.673%	1.085%	1.015%	1.009%	1.030%	0.859%	0.922%	0.647%	0.479%	0.557%
		0.006	***0.007***	***0.004***	***0.079***	***0.096***	***0.090***	***0.094***	*0.160*	***0.124***	*0.296*	*0.433*	*0.358*
	LF2	1.621%	1.682%	1.634%	1.228%	1.313%	1.213%	1.082%	1.048%	1.040%	0.806%	0.841%	0.836%
		0.004	***0.002***	***0.003***	***0.036***	***0.021***	***0.029***	***0.063***	***0.065***	***0.060***	*0.172*	*0.133*	*0.131*
	LF1	1.387%	1.630%	1.598%	1.190%	1.366%	1.320%	1.183%	1.131%	1.156%	0.943%	0.882%	0.939%
		0.010	***0.002***	***0.002***	***0.030***	***0.009***	***0.011***	***0.028***	***0.031***	***0.025***	***0.092***	***0.090***	***0.070***

Table 3.1: Momentum test portfolio excess returns assuming equal weighting and no gap between portfolio estimation and holding period. Each 3 x 3 square within the table represents average momentum excess returns in a percentage form as well as italicized p-values that are emboldened when significant at the 10%, 5% and 1% level

Considering only the extreme liquidity filter portfolios, 63% of the high liquidity portfolio excess returns outperform their low liquidity counterparts by 0.075% per month, with the differential not being significantly different zero. The relationship seems to switch as the assumed holding period increases beyond six months as excess momentum returns seem to increase as the liquidity filter is relaxed, with 83% of low liquidity excess returns outperforming their high liquidity counterparts, producing 0.21% additional monthly return and is significant at the 1% level. The regime change experienced over the holding periods is possibly consistent with the findings of Lee and Swaminathan (2000) as the authors found that highly liquid winners and losers tend to reverse faster than their less liquid counterparts. The results expressed in Table 3.1 may be a result of excess momentum returns not experiencing reversal at shorter investment horizons (holding periods between three and six months) while reversals become more prevalent at longer investment horizons. The findings are also partly consistent with the more recent study by Page, Britten and Auret (2013) where the authors found that momentum maintains a positive relationship with liquidity as higher liquidity allows for greater levels of underreaction.

The effects of the price filter are more profound as irrespective of holding period, estimation period and liquidity filter, momentum profits generally seem to decrease given the application of an escalating price filter, implying that momentum profits maintain a negative relationship with direct transaction costs. Considering only the extreme price filter excess portfolio returns, irrespective of the estimation and holding period, 67% of the low price filter excess returns outperform their high price filter counterparts, providing 0.068% additional monthly excess return and is significant at the 5% level. The findings are consistent with those of Lesmond, Schill and Zhou (2004) and Korajczyk and Sadka (2004), where both studies found that momentum profits maintain a negative relationship with the direct cost of trading. The implication of the findings per Table 3.1 cast potential doubt on the paper profits achieved using momentum strategies on the JSE, however, when considering the 6;6 momentum portfolio, at the highest price filter, excess returns are between 1.27% and 1.42% per month and significant at the 1% and 5% level respectively. The results are therefore also consistent with Muller and Ward (2013) who found that the momentum premium is positive and significant even when considering a universe of shares listed on the JSE limited to the top 100 based on market capitalization, assuming that price is positively correlated with market capitalization. In order to summarize the findings of the test portfolio simulations presented in Table 3.1, Table 3.2 below describes the average excess return, average p-value (italicized) and number of significant (emboldened) excess returns per the nine simulations conducted within each portfolio estimation and holding period.

E:H	3	6	9	12
3	0.7837%	1.0628%	1.1752%	0.8781%
	0.1876	*0.0634**	*0.0383***	*0.1329*
	[0]	***[3]***	***[7]***	***[4]***
6	1.2398%	1.4042%	1.7949%	1.1699%
	*0.0310***	*0.0130***	*0.0012****	*0.0377***
	[8]	***[9]***	***[9]***	***[9]***
9	1.5056%	1.4270%	1.1319%	1.1876%
	*0.0081****	*0.0143***	*0.0441***	*0.0526**
	[9]	***[9]***	***[7]***	***[8]***
12	1.6069%	1.1933%	1.0502%	0.7699%
	*0.0045****	*0.0453***	*0.0721**	*0.1972*
	[9]	***[9]***	***[7]***	***[3]***

Table 3.2: Average excess returns, p-values (,**,*** indicating significance at 10%, 5% and 1% level) and number of significant simulations assuming equal weighting and no gap between portfolio estimation and holding period*.

Table 3.2 summarizes the findings presented in Table 3.1 in terms of the average excess returns for each of the portfolio simulations and the number of statistically significant portfolio simulations within the assumed estimation and holding period. The emboldened numbers below the italicized p-values represent the total number of significant permutations, where the maximum number of permutations is equal to nine based on three price and liquidity filters. In terms of absolute percentage returns, the best performing momentum test portfolios are achieved by the 6;9 portfolios, achieving 1.795% per month (21.54% per annum) on average and are significant at the 1% level. Furthermore, the 6;9 test portfolios are significantly positive in all nine simulations based on variations in price and liquidity filters. The second best performing test portfolio is the 12;3 portfolios, achieving excess average returns of 1.607% per month (19.28% per annum) across simulations and is significant at the 1% level. The findings are highly similar to those of van Rensburg (2001) and more recently Muller and Ward (2013), where both studies found the 12;3 momentum portfolio to be the most profitable style based portfolio.

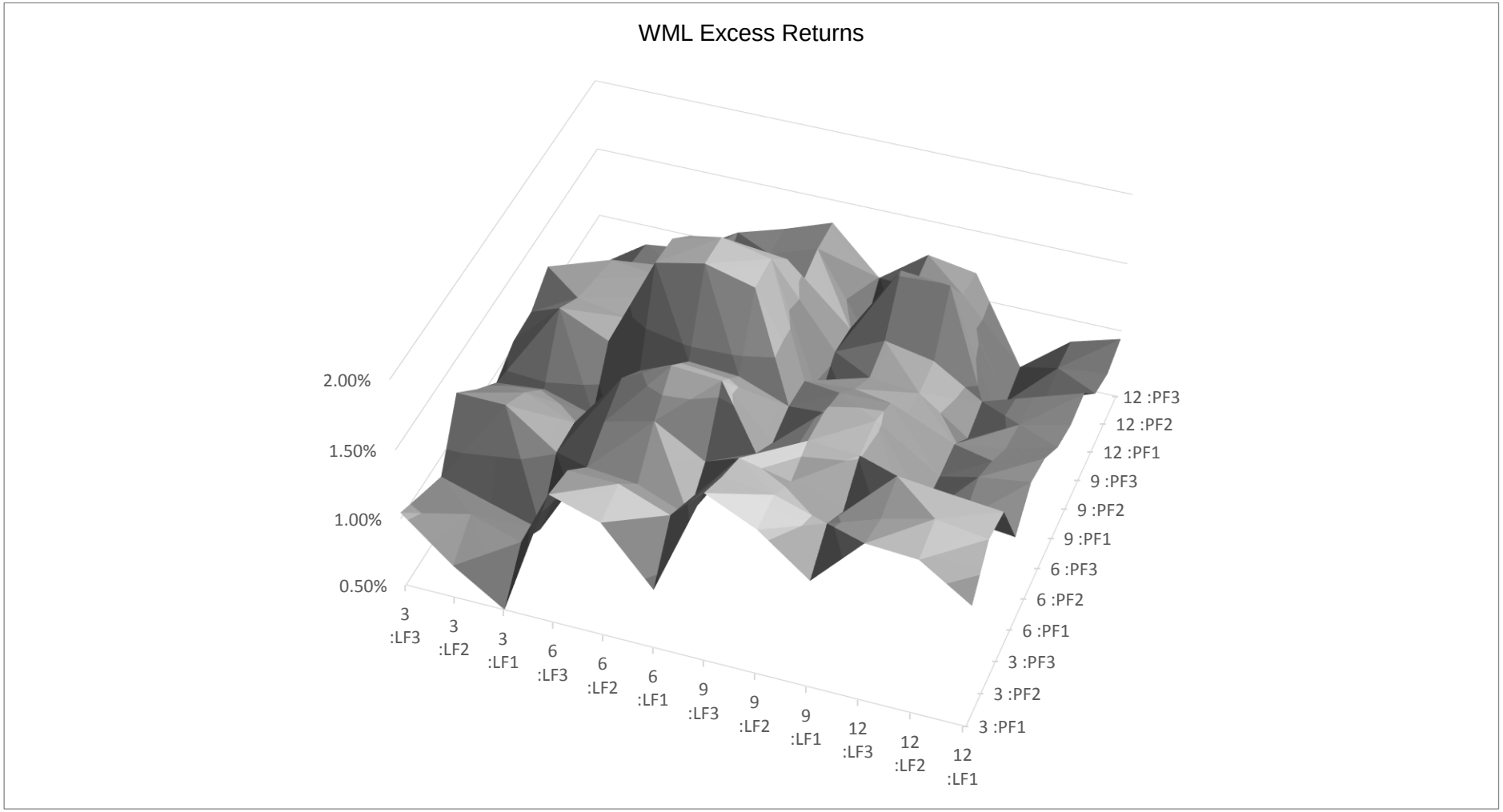


Figure 3.2: Surface diagram of equally weighted excess momentum profits allowing for variations in liquidity and price filter

3.4.2 Excess momentum profits assuming value weighting and no gap between estimation and holding period

Table 3.3 provides the overall results of the momentum portfolio sorts assuming value weighting with no gap between portfolio estimation and holding period. In order to define a high level view of the value weighted momentum profits, the excess returns are displayed in Figure 3.3, depicting excess returns given changes in portfolio estimation and holding periods. Most notably, the surface diagram is distinctly flatter, implying that momentum returns decrease when applying value weighting to momentum sorts. Like the equally weighted results, when considering estimation periods between three and six months, excess returns tend to increase between holding periods of three and nine months but decrease thereafter. Once again, the highest returns seem to be clustered around the estimation and holding periods of between six and nine months barring the relatively large excess return achieved by the 12 month estimation; three month holding period. Considering variations in holding periods, at a holding period of three months, excess portfolio returns increase monotonically given an increase in the portfolio estimation period. Conversely, for portfolio holding periods between six to twelve months, portfolio excess returns increase between estimation periods of three and six months and tend to decrease thereafter. Table 3.3 displays the results of the value weighted momentum test portfolios allowing for variations in both price and liquidity filters. Confirming the results presented in the Figure 3.3, market capitalization weighting has a negative effect on excess momentum profits, as excess returns are both economically lower and statistically less significant. Out of 144 simulations, only 25 momentum excess returns are statistically significant at the 5% level. Once again, the application of price and liquidity filters does seem to result in variation in value weighted excess momentum returns (see figure 3.4).

Focusing on variations in liquidity, value weighted momentum excess returns seem less sensitive to changes in the liquidity filter and do not display any distinct relationship, irrespective of portfolio estimation and holding periods. A possible reason for this is that the effect of value weighting naturally up-weights large market capitalization shares that are typically more liquid than their small capitalization counterparts. Conversely, the effects of the price filter on value weighted excess momentum returns is more apparent irrespective of liquidity filter, estimation and holding period. The results are practically identical to those of the equally weighted momentum excess returns as momentum seems to maintain a negative relationship with transaction costs, however, the relationship strangely does not hold for the six month estimation and holding period momentum sorts as portfolio returns seem to be consistent irrespective of the price filter applied.

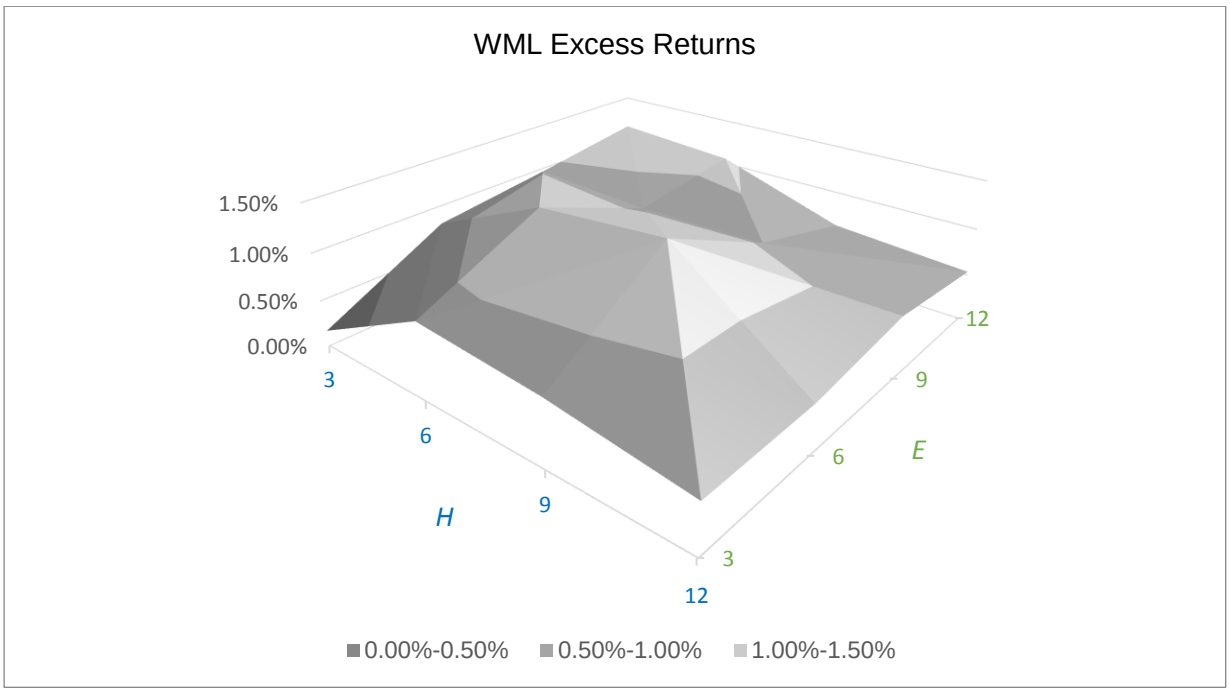


Figure 3.3: Excess Momentum returns assuming value weighting and no gap between portfolio estimation and holding period where E and H represent the assumed portfolio estimation and holding periods

Considering the low (PF1) and high transaction cost (PF3) filters, across all portfolio simulations, 77% of the low transaction cost momentum excess returns are higher than their high transaction cost counterparts, but the inverse holds for the six month estimation and holding period portfolio as all of the high transaction cost simulation portfolios outperform their low transaction cost counterparts. Table 3.4 below depicts a summarized version of Table 3.3 where the various test portfolio excess returns per estimation and holding period, average p-value and number of significant simulations are presented.

Table 3.4 further reiterates the effect of value-weighting on momentum returns. Irrespective of estimation and holding period, momentum profits are economically lower and less significant in comparison to the equivalent equally weighted momentum portfolios. When comparing the results of the value weighted excess returns to their equivalent equally weighted counterparts, equally weighted excess returns are on average 0.38% higher per month and the difference is significant at the 1% level. Furthermore, of the 144 simulations estimated assuming equal weighting, 110 of the excess returns are significantly different from zero at the 5% level while of the 144 value weighted test portfolio excess returns, only 25 are significantly different from zero at the 5% level.

E	H	3			6			9			12		
		PF1	PF2	PF3	PF1	PF2	PF3	PF1	PF2	PF3	PF1	PF2	PF3
3	LF3	0.376%	0.172%	0.148%	0.843%	0.730%	0.640%	0.760%	0.723%	0.692%	0.531%	0.482%	0.391%
		0.589	*0.802*	*0.831*	*0.202*	*0.266*	*0.331*	*0.298*	*0.318*	*0.339*	*0.414*	*0.458*	*0.543*
	LF2	0.290%	0.064%	0.030%	0.940%	0.792%	0.732%	0.723%	0.644%	0.734%	0.644%	0.436%	0.407%
		0.667	*0.925*	*0.964*	*0.150*	*0.224*	*0.262*	*0.315*	*0.368*	*0.306*	*0.323*	*0.490*	*0.519*
	LF1	0.286%	0.097%	0.065%	1.025%	0.898%	0.784%	0.712%	0.689%	0.708%	0.802%	0.521%	0.464%
		0.668	*0.886*	*0.923*	*0.111*	*0.159*	*0.223*	*0.317*	*0.324*	*0.317*	*0.220*	*0.406*	*0.461*
6	LF3	0.972%	0.793%	0.662%	1.301%	1.273%	1.358%	1.659%	1.617%	1.470%	0.403%	0.544%	0.736%
		0.177	*0.263*	*0.345*	***0.055***	***0.054***	***0.038***	***0.015***	***0.016***	***0.027***	*0.528*	*0.387*	*0.240*
	LF2	0.922%	0.791%	0.788%	1.372%	1.399%	1.530%	1.730%	1.466%	1.388%	0.234%	0.423%	0.682%
		0.210	*0.275*	*0.263*	***0.046***	***0.037***	***0.018***	***0.012***	***0.030***	***0.037***	*0.720*	*0.510*	*0.279*
	LF1	0.846%	0.746%	0.729%	1.283%	1.416%	1.484%	1.610%	1.448%	1.348%	0.385%	0.499%	0.742%
		0.244	*0.296*	*0.298*	***0.058***	***0.032***	***0.021***	***0.019***	***0.030***	***0.042***	*0.553*	*0.438*	*0.236*
9	LF3	0.988%	0.889%	0.881%	0.706%	0.716%	0.771%	0.889%	0.826%	0.948%	0.614%	0.598%	0.536%
		0.146	*0.190*	*0.191*	*0.286*	*0.283*	*0.244*	*0.178*	*0.215*	*0.148*	*0.360*	*0.356*	*0.403*
	LF2	1.150%	0.841%	0.912%	1.125%	1.036%	0.932%	0.975%	0.886%	0.949%	0.814%	0.728%	0.646%
		0.091	*0.208*	*0.169*	***0.086***	*0.110*	*0.151*	*0.141*	*0.171*	*0.140*	*0.214*	*0.250*	*0.309*
	LF1	1.224%	0.895%	0.899%	0.918%	0.995%	0.916%	1.056%	0.923%	0.977%	0.681%	0.753%	0.609%
		0.071	*0.175*	*0.172*	*0.166*	*0.119*	*0.154*	*0.111*	*0.151*	*0.125*	*0.292*	*0.231*	*0.334*
12	LF3	1.245%	0.940%	1.038%	0.933%	0.927%	0.824%	0.484%	0.433%	0.546%	0.489%	0.462%	0.454%
		0.077	*0.169*	*0.124*	*0.176*	*0.174*	*0.224*	*0.485*	*0.530*	*0.423*	*0.468*	*0.491*	*0.499*
	LF2	1.257%	1.219%	1.072%	1.157%	1.104%	1.017%	0.600%	0.668%	0.583%	0.656%	0.466%	0.448%
		0.070	***0.073***	*0.104*	***0.090***	***0.099***	*0.122*	*0.376*	*0.323*	*0.382*	*0.323*	*0.479*	*0.488*
	LF1	1.235%	1.219%	1.065%	1.213%	1.174%	1.143%	0.637%	0.824%	0.864%	0.702%	0.556%	0.577%
		0.070	***0.068***	*0.101*	***0.072***	***0.073***	***0.079***	*0.348*	*0.210*	*0.190*	*0.287*	*0.390*	*0.371*

Table 3.3: Momentum test portfolio excess returns assuming market capitalization weighting and no gap between portfolio estimation and holding period. Each 3 x 3 square within the table represents average momentum excess returns in a percentage form as well as italicized p-values that are emboldened when significant at the 10%, 5% and 1% level

E:H	3	6	9	12
3	0.1697%	0.8203%	0.7096%	0.5198%
	0.8060	*0.2142*	*0.3224*	*0.4259*
	[0]	***[0]***	***[0]***	***[0]***
6	0.8055%	1.3798%	1.5263%	0.5164%
	0.2633	*0.0397***	*0.0253***	*0.4324*
	[0]	***[6]***	***[9]***	***[0]***
9	0.9643%	0.9017%	0.9367%	0.6643%
	0.1570	*0.1777*	*0.1533*	*0.3056*
	[0]	***[0]***	***[0]***	***[0]***
12	1.1433%	1.0547%	0.6267%	0.5343%
	*0.0951**	*0.1233*	*0.3630*	*0.4218*
	[5]	***[5]***	***[0]***	***[0]***

Table 3.4: Average excess returns, p-values (,**,*** indicating significance at 10%, 5% and 1% level) and number of significant simulations assuming value weighting and no gap between estimation and holding period*

Once again, assuming value weighting and no gap between portfolio estimation and holding period, the six month estimation period produced the highest excess returns assuming holding periods of six and nine months (6;6 and 6;9), achieving 1.38% (16.56% on an annualized basis) and 1.53% per month (18.31% annualized) on average respectively. Consistent with the findings of van Rensburg (2001) and Muller and Ward (2013), the 12;3 portfolio performed well, achieving the third highest average excess return of 1.14% per month (13.72%) and was just significant at the 10% level. The findings are consistent with both Lewellen (2002) and Korajcyk and Sadka (2004) who found that value weighting negatively effects momentum returns. In relation to South African literature, Basiewicz and Auret (2009) found that both the value and size effect are reduced when value-weighting returns. A further potential reason behind the relatively poorer performance of the value-weighted excess returns could be the size effect of Banz (1981) as value-weighting by construction results in larger market capitalization momentum shares receiving a higher relative in-portfolio weighting (The link between momentum and size will be explored in Chapter Four that follows).

Lastly, the worst performing test portfolio was the 3;3 portfolio, which achieved an insignificant excess return of just 0.17% per month. The next worst performing test portfolios were confined to the 12;12 portfolio. The poor performance potentially lends credence to the findings of Jegadeesh (1990), Jegadeesh and Titman (1991) and Debondt and Thaler (1985, 1989) who found reversal

in share prices tend to occur at extremely short and long horizons, typically less than one month and more than six months. Both three and twelve months are the extreme ends of the intermediate medium-term horizon spectrum, hence the results may be a manifestation of short and long-term reversal. In conjunction with the reversal explanation, and as mentioned previously, since value weighting typically results in increased liquidity, portfolios simulations could experience higher level of reversal consistent with the findings of Lee and Swaminathan (2000).

3.4.3 Excess momentum profits assuming equal weighting and a one month gap between estimation and holding period

The majority of momentum studies utilize the portfolio formation methodology described by Jegadeesh and Titman (1993, 2001) allowing for a period of time between the sorting of shares cross-sectionally and the initiation of investment (forming of portfolios) post cross-sectional classification. Jegadeesh and Titman (1993) found that the inclusion of a single month gap between portfolio estimation and holding period/investment uniformly increased the momentum premium, lending credence to the findings of Jegadeesh (1990), Lehmann (1990) and Jegadeesh and Titman (1991) as all found that reversal in share prices tended to occur over extremely short time horizons (in addition to extremely long horizons as per Debondt and Thaler (1985)). The South African literature on momentum has typically not been as methodologically pedantic, as the majority of the literature reviewed failed to empirically incorporate an allowance for a “gap” between sorting and investment periods. In order to test whether microstructure effects or short-term reversal negatively affect momentum returns applied to the cross-section of shares listed on the JSE, test portfolio simulations are re-run allowing for a single month gap between portfolio estimation and holding periods.

The methodology of Asness (1997) is applied where the portfolio estimation periods used (*E*) are still three, six, nine and twelve months. Additionally, the most recent month is excluded, therefore becoming *E*-1 and resulting in a one month gap between the determination of portfolio quintiles and investment. Over and above the analysis of portfolio performance in terms of estimation and holding period and variations in price and liquidity filters, the final test will be the direct comparison of the equally and value weighted no gap (“no-gap” hereafter) excess returns to their counterparts that allow for a gap (“gapped” hereafter) between portfolio estimation and holding period. Tables 3.5 and 3.6 present the expanded and summarized version of the equally weighted momentum portfolio simulations allowing for a one month gap between estimation and holding period initiation.

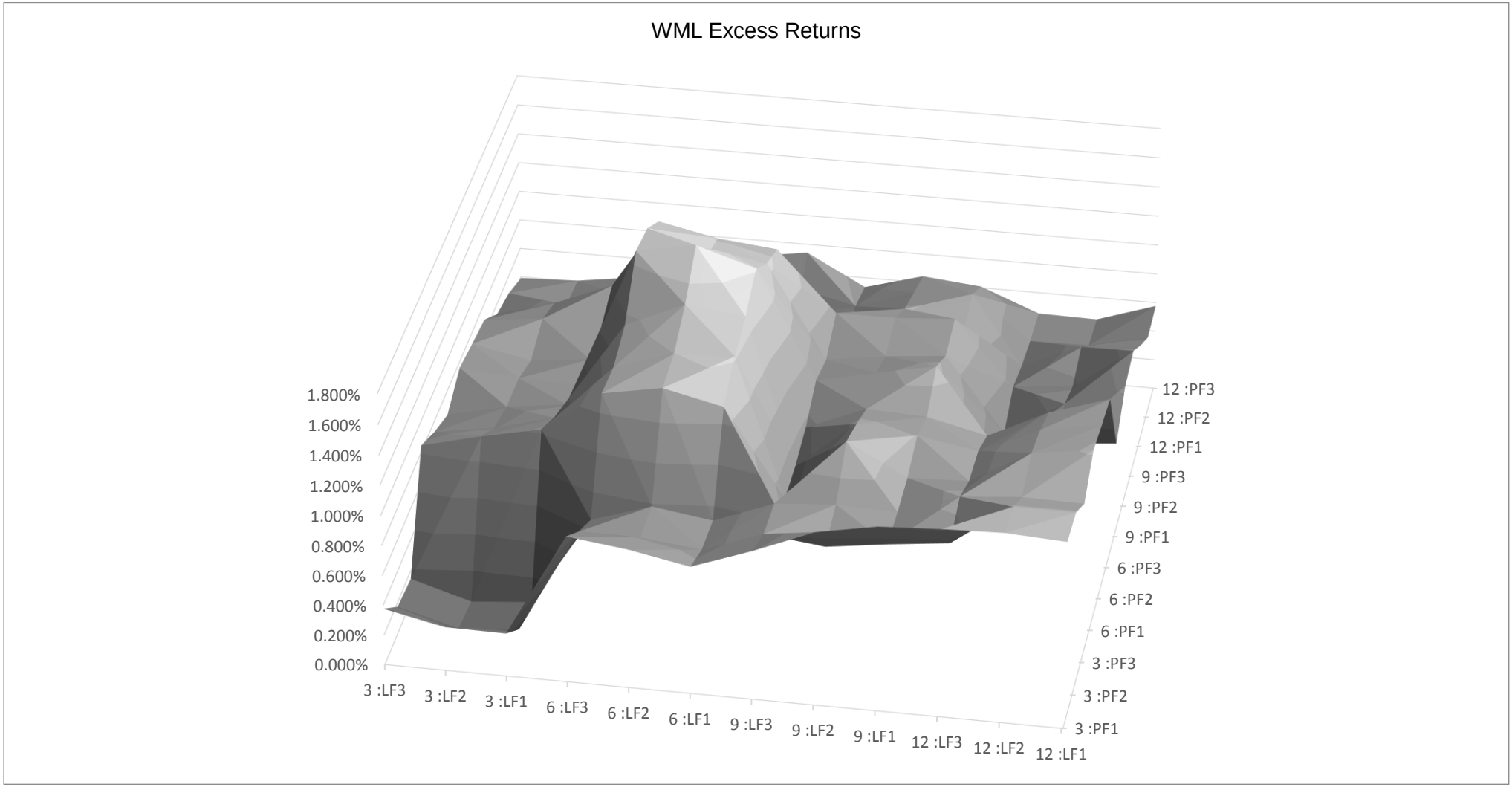


Figure 3.4: Surface diagram of value weighted excess momentum profits allowing for variations in liquidity and price filter

E	H	3			6			9			12		
		PF1	PF2	PF3	PF1	PF2	PF3	PF1	PF2	PF3	PF1	PF2	PF3
3	LF 3	1.539%	1.441%	1.265%	1.463%	1.268%	0.995%	1.142%	1.067%	1.087%	1.254%	1.043%	0.983%
		0.0081	***0.0126***	***0.0290***	***0.0112***	***0.0289***	***0.0845***	***0.0484***	***0.0605***	***0.0537***	***0.0342***	***0.0746***	***0.0930***
	LF 2	1.643%	1.550%	1.355%	1.214%	1.091%	0.885%	1.174%	1.044%	0.912%	1.339%	1.112%	1.045%
		0.0028	***0.0039***	***0.0118***	***0.0301***	***0.0440***	*0.1008*	***0.0331***	***0.0451***	***0.0789***	***0.0233***	***0.0415***	***0.0564***
	LF 1	1.394%	1.497%	1.280%	1.084%	1.004%	0.748%	1.106%	0.918%	0.760%	1.224%	1.160%	1.044%
		0.0078	***0.0032***	***0.0124***	***0.0397***	***0.0464***	*0.1410*	***0.0305***	***0.0598***	*0.1194*	***0.0264***	***0.0229***	***0.0434***
6	LF 3	1.571%	1.351%	1.173%	1.308%	1.363%	1.245%	1.844%	1.720%	1.556%	1.347%	1.285%	1.323%
		0.0073	***0.0195***	***0.0433***	***0.0198***	***0.0157***	***0.0250***	***0.0010***	***0.0018***	***0.0049***	***0.0161***	***0.0177***	***0.0163***
	LF 2	1.568%	1.484%	1.299%	1.277%	1.511%	1.378%	1.830%	1.776%	1.624%	1.527%	1.428%	1.439%
		0.0043	***0.0058***	***0.0160***	***0.0174***	***0.0044***	***0.0084***	***0.0006***	***0.0005***	***0.0017***	***0.0046***	***0.0055***	***0.0061***
	LF 1	1.351%	1.471%	1.263%	1.173%	1.500%	1.330%	1.785%	1.725%	1.623%	1.610%	1.516%	1.522%
		0.0100	***0.0038***	***0.0137***	***0.0218***	***0.0024***	***0.0066***	***0.0005***	***0.0004***	***0.0011***	***0.0024***	***0.0021***	***0.0024***
9	LF 3	1.565%	1.309%	1.293%	1.597%	1.464%	1.393%	1.375%	1.097%	1.117%	1.323%	1.182%	1.230%
		0.0086	***0.0240***	***0.0237***	***0.0062***	***0.0106***	***0.0144***	***0.0176***	***0.0508***	***0.0440***	***0.0241***	***0.0363***	***0.0313***
	LF 2	1.576%	1.451%	1.370%	1.760%	1.581%	1.551%	1.391%	1.085%	1.150%	1.802%	1.378%	1.422%
		0.0042	***0.0068***	***0.0103***	***0.0016***	***0.0031***	***0.0037***	***0.0124***	***0.0380***	***0.0271***	***0.0018***	***0.0088***	***0.0076***
	LF 1	1.488%	1.519%	1.358%	1.815%	1.705%	1.624%	1.328%	1.156%	1.173%	1.698%	1.414%	1.414%
		0.0047	***0.0026***	***0.0073***	***0.0007***	***0.0007***	***0.0013***	***0.0106***	***0.0179***	***0.0156***	***0.0018***	***0.0046***	***0.0054***
12	LF 3	1.584%	1.478%	1.440%	1.205%	1.095%	1.145%	0.987%	0.813%	0.855%	0.596%	0.516%	0.628%
		0.0077	***0.0114***	***0.0131***	***0.0482***	***0.0707***	***0.0525***	*0.1032*	*0.1767*	*0.1459*	*0.3323*	*0.3950*	*0.2931*
	LF 2	1.497%	1.568%	1.475%	1.210%	1.347%	1.303%	0.861%	0.954%	0.879%	0.770%	0.922%	0.912%
		0.0071	***0.0041***	***0.0067***	***0.0362***	***0.0166***	***0.0182***	*0.1328*	***0.0832***	*0.1057*	*0.1914*	***0.0961***	***0.0971***
	LF 1	1.380%	1.564%	1.445%	1.185%	1.397%	1.366%	0.927%	0.975%	1.007%	0.817%	0.917%	0.977%
		0.0094	***0.0022***	***0.0047***	***0.0307***	***0.0073***	***0.0083***	***0.0832***	***0.0547***	***0.0452***	*0.1470*	***0.0761***	***0.0588***

Table 3.5: Momentum test portfolio excess returns assuming equal weighting and a single month gap between portfolio estimation and holding period. Each 3 x 3 square within the table represents average momentum excess returns in a percentage form as well as italicized p-values that are emboldened when significant at the 10%, 5% and 1% level

E:H	3	6	9	12
3	1.4407%	1.0837%	1.0233%	1.1337%
	*0.0102***	*0.0585**	*0.0588**	*0.0462***
	[9]	***[6]***	***[4]***	***[6]***
6	1.3922%	1.3429%	1.7203%	1.4443%
	*0.0137***	*0.0135***	*0.0014****	*0.0081****
	[9]	***[9]***	***[9]***	***[9]***
9	1.4366%	1.6100%	1.2079%	1.4292%
	*0.0103***	*0.0047****	*0.0260***	*0.0135***
	[9]	***[9]***	***[8]***	***[9]***
12	1.4924%	1.2503%	0.9177%	0.7839%
	*0.0074****	*0.0321***	*0.1034*	*0.1874*
	[9]	***[7]***	***[1]***	***[0]***

Table 3.6: Average excess returns, p-values (,**,*** indicating significance at 10%, 5% and 1% level) and number of significant simulations assuming equal weighting and a one-month gap between portfolio estimation and holding period*

The results of the one month allowance between portfolio estimation and holding period seems to have a positive effect on momentum returns when compared to the original “no-gap” simulations. Considering the summarized results of table 3.5 presented in table 3.6, throughout all the estimation and holding periods, not only are momentum excess returns positive, but only two portfolio simulations achieve excess returns below 1% per month, namely the 12:9 and 12:12 portfolios. Further, the 3;3 momentum portfolio produces excess returns of 1.44% per month on average and is significant at the 5% level. This is a vast improvement when compared to the momentum simulations run without an allowance for a gap between portfolio estimation and holding period.

Table 3.5 displays the test portfolio simulations allowing for variations in liquidity and transaction costs proxied by zero daily trades, turnover and price. Like the original “no-gap” test portfolio simulations, momentum excess returns seems to maintain a weak relationship with liquidity. Considering only the extreme highest liquidity test portfolios versus the lowest, the high liquidity excess returns are greater than their low liquidity counterparts 58% of the time, however the percentage difference in average excess returns is not significantly different from zero. Interestingly, the largest proportion of the high liquidity momentum excess returns beating their lower liquidity counterparts occurs in the three month estimation period (77%) but decreases when considering estimation periods between six and twelve months (22%-33%). Conversely, the effects of transaction costs, proxied by the natural logarithm of price, seem to maintain a consistently negative relationship with momentum returns. Considering simulations run assuming

the most lenient and stringent price filters only (PF1 and PF3), 79% of the lenient price filter momentum excess average returns exceed those of their more stringent counterparts and the difference of 0.143% per month is significantly different from zero at the 5% level. Interestingly, of the remaining 21% where the more stringent price filter simulations outperform, all are confined to the portfolio estimation period of twelve months.

The results therefore indicate that the even when allowing for a month gap between portfolio estimation and investment, momentum excess returns tend to be less sensitive to liquidity effects and at best display a weakly positive relationship with liquidity. However, irrespective of methodological variations, momentum tends to display negative relationship with transaction costs, where momentum excess returns are highly sensitive to the transaction costs attributable to the constituent shares within the extreme winner and loser portfolios. Such results have implications for the application of momentum and the costs of engaging in such a strategy on the cross-section of shares listed on the JSE. Pontiff (1996) asserted that direct transaction costs may perpetuate the existence of pricing anomalies. The results presented provide evidence in favor of the 'limits to arbitrage' hypothesis and will be explored in the chapters that follow.

A core question that requires address is whether the momentum profits on the cross-section of shares on the JSE are effected by short term-reversal and bid/ask bounce as noted by Jegadeesh (1990), Lehmann (1990) and Jegadeesh and Titman (1993). A simple test is conducted where the original no-gap equally weighted simulation results are compared to the second set of simulations that assumed equal weighting and allowed for a single month gap between portfolio estimation and holding periods. In initial equally weighted no-gap simulations (144 simulations in total), the average momentum excess return was 1.21% per month and significant at the 5% level. The average excess return increased to 1.294% when allowing for the single month gap, where out of 144 simulations, 57% (or 82) of the gapped excess momentum returns were greater than their no-gap counterparts. The dynamics of the differences are of interest when allowing for variation in portfolio estimation and holding periods. Considering variations in estimation periods, the difference between gapped and no-gap excess returns is highest assuming an estimation period of three months and lowest when assuming an estimation period of twelve months.

The result is intuitive as one would logically expect that the allowance of a one month gap would have a greater effect on shorter estimation periods. A more definitive relationship emerges when considering the difference in momentum excess returns attributable to the application of a gap between portfolio estimation and holding period in relation to portfolio holding periods. At portfolio holding periods of three and twelve months, gapped excess returns are significantly greater (0.156% and 0.196% on average), while at portfolio holding periods of six and nine months, there is no significant difference between no gap and gapped momentum excess returns. The results therefore indicate that the methodological variation of allowing for a gap between portfolio

estimation and holding periods tends to only impact momentum profits when assuming portfolio holding periods of three and twelve months.

The results of the secondary set of equally weighted momentum simulations dictate that the effects of an allowance of a gap between portfolio estimations and holding periods does not significantly impact momentum profits and on average only contributes an additional 0.083% per month. However, the impact of the methodological variation is significant when considering the estimation and holding periods of three and twelve months. On a nominal basis, the results are consistent with Jegadeesh and Titman (1993) as momentum profits are economically higher when applying the methodological variation of skipping the most recent month within the portfolio estimation period. Lastly, the results provide evidence of reversal over extremely short time-frames as per Jegadeesh (1990), Lehmann (1990) and Jegadeesh and Titman (1991).

The biggest improvement in portfolio average excess return (when allowing for a gap) is found in the three month estimation and holding period test portfolio, implying that the three month estimation and holding period portfolio is the most susceptible to short-term reversal. The outcome is logical as the three month estimation and holding period portfolio should be the most susceptible to short-term reversal being the smallest window period considered within the portfolio simulation exercise.

3.4.4 Excess momentum profits assuming value weighting and a one month gap between estimation and holding period

The results of value weighted momentum returns assuming no gap between portfolio estimation and holding period were significantly lower than their equivalent equally weighted counterparts, consistent with the findings of Lewellen (2002) and Korajcyk and Sadka (2004) who found that value weighting negatively effects momentum profits. In order to determine the impact of the methodological variation of skipping the most recent month in the portfolio estimation period, the value weighted momentum test portfolio simulations are rerun allowing for a single month gap between portfolio estimation and holding period and will be compared with their ‘no-gap’ counterparts. Emphasis is placed on the fact that value weighting naturally tilts the momentum portfolios to constituent shares that are both larger in terms of market capitalization and are probably more liquid on a cross sectional basis. Lee and Swaminathan (2000) found that highly liquid historical winner and loser shares experienced accelerated reversal when compared to less historical winners and losers, leading the authors to develop an augmented momentum strategy that bought low liquidity historical winner shares and simultaneously shorted highly liquid historical losers.

The implications of their study are pertinent to the current test as the value weighted momentum returns have a natural and indirect loading on the more liquid constituent shares within portfolio sorts. If liquidity does indeed maintain a positive relationship with reversal, the effects of allowing for a single month gap between portfolio estimation and investment should result in increased momentum profits as a central purpose of the single month gap is to mitigate the effects of short-term reversal in share prices as expressed by Jegadeesh (1990), Lehmann (1990) and Jegadeesh and Titman (1991). Tables 3.7 and 3.8 depict the momentum excess returns for the value weighted momentum test portfolios that allow for a gap between estimation and holding periods.

Prior to comparing the results of the no-gap and gapped value weighted momentum test portfolios, the dynamics of momentum profits in terms of estimation period, holding period, liquidity and transaction costs will be examined. The results presented in Table 3.8 indicate that, consistent across all simulations, the highest momentum returns are achieved assuming estimation and holding periods of between six and nine months. Consistent with the results of the equally weighted gapped simulations, the three month estimation and holding period performs significantly better, achieving an excess average monthly return of 1.296%. Considering the effects of a variation in the applied estimation period, assuming a portfolio holding period of three months, momentum excess returns decrease monotonically as the estimation period increases, however, excess average returns are all greater than 1% per month and statistically significant. The pattern changes slightly when holding periods increase between six to twelve months, as all display an increase in momentum profits as the assumed estimation period increases from three to six months and decrease thereafter.

Considering the results presented in Table 3.7, the effects of the liquidity filter on momentum excess returns is inconsistent with the previous findings related to the equally weighted gapped momentum excess returns. Considering only the extreme liquidity filters (LF1 and LF3), 77% of the low liquidity momentum excess returns are greater than their high liquidity counterparts, with the difference of 0.136% being significant at the 10% level. The increased sensitivity to liquidity may be attributable to the interaction between liquidity and size, as momentum portfolios are naturally weighted towards more liquid large capitalization shares. Shifting focus to the variation in price filters or transaction costs, the results of the value weighted gapped momentum excess returns are consistent with all the previous results presented, namely that momentum excess returns maintain a negative relationship with transaction costs. Comparing only the extreme price filters (PF1 and PF3), the low transaction cost momentum average returns exceed their high transaction cost counterparts in 88% of simulations and the percentage difference in excess returns of 0.108% is significant at the 5% level.

	H	3			6			9			12		
E		**PF1**	**PF2**	**PF3**	**PF1**	**PF2**	**PF3**	**PF1**	**PF2**	**PF3**	**PF1**	**PF2**	**PF3**
3	**LF3**	1.304%	1.066%	1.115%	0.914%	0.906%	0.910%	0.844%	0.670%	0.693%	0.561%	0.560%	0.572%
		0.0570	*0.1170*	*0.1067*	*0.1590*	*0.1527*	*0.1488*	*0.2392*	*0.3410*	*0.3139*	*0.3897*	*0.3788*	*0.3684*
	LF2	1.532%	1.245%	1.364%	0.977%	0.930%	0.954%	0.626%	0.676%	0.485%	0.809%	0.653%	0.634%
		0.0248	***0.0631***	***0.0412***	*0.1221*	*0.1389*	*0.1263*	*0.3792*	*0.3321*	*0.4496*	*0.2070*	*0.3002*	*0.3134*
	LF1	1.467%	1.271%	1.300%	1.117%	0.940%	0.840%	0.814%	0.757%	0.411%	1.015%	0.703%	0.619%
		0.0288	***0.0537***	***0.0499***	***0.0754***	*0.1296*	*0.1728*	*0.2464*	*0.2746*	*0.5163*	*0.1146*	*0.2586*	*0.3173*
6	**LF3**	1.171%	0.954%	0.996%	1.127%	1.074%	1.142%	1.541%	1.507%	1.390%	0.877%	0.790%	0.955%
		0.0879	*0.1611*	*0.1499*	***0.0733***	***0.0910***	***0.0667***	***0.0198***	***0.0257***	***0.0364***	*0.1652*	*0.2003*	*0.1232*
	LF2	1.412%	1.123%	1.244%	1.386%	1.342%	1.309%	1.701%	1.474%	1.460%	0.960%	0.804%	0.942%
		0.0388	***0.0941***	***0.0627***	***0.0239***	***0.0311***	***0.0308***	***0.0092***	***0.0241***	***0.0245***	*0.1387*	*0.1896*	*0.1282*
	LF1	1.379%	1.184%	1.220%	1.404%	1.230%	1.307%	1.486%	1.422%	1.356%	0.896%	0.763%	0.850%
		0.0405	***0.0734***	***0.0667***	***0.0192***	***0.0455***	***0.0307***	***0.0211***	***0.0289***	***0.0360***	*0.1666*	*0.2189*	*0.1727*
9	**LF3**	0.912%	1.051%	1.044%	1.025%	1.091%	1.053%	1.056%	1.121%	1.115%	0.876%	0.777%	0.745%
		0.1777	*0.1093*	*0.1077*	*0.1289*	***0.0974***	*0.1093*	*0.1175*	***0.0874***	***0.0858***	*0.1968*	*0.2339*	*0.2545*
	LF2	1.135%	1.186%	1.134%	1.226%	1.167%	1.179%	1.225%	1.069%	1.173%	1.007%	0.805%	0.864%
		0.0903	***0.0669***	***0.0771***	***0.0675***	***0.0737***	***0.0692***	***0.0625***	***0.0982***	***0.0660***	*0.1275*	*0.2083*	*0.1758*
	LF1	1.286%	1.115%	1.119%	1.312%	1.173%	1.186%	1.209%	1.092%	1.106%	1.028%	0.892%	0.934%
		0.0544	***0.0812***	***0.0779***	***0.0488***	***0.0684***	***0.0631***	***0.0642***	***0.0883***	***0.0795***	*0.1108*	*0.1598*	*0.1427*
12	**LF3**	1.104%	1.012%	1.007%	0.905%	0.687%	0.738%	0.451%	0.380%	0.402%	0.293%	0.291%	0.215%
		0.1057	*0.1338*	*0.1358*	*0.1949*	*0.3200*	*0.2815*	*0.5086*	*0.5669*	*0.5480*	*0.6710*	*0.6673*	*0.7456*
	LF2	1.160%	1.150%	1.014%	1.034%	1.071%	0.897%	0.522%	0.534%	0.456%	0.412%	0.531%	0.338%
		0.0863	***0.0848***	*0.1294*	*0.1278*	*0.1102*	*0.1797*	*0.4388*	*0.4170*	*0.4854*	*0.5396*	*0.4106*	*0.5978*
	LF1	1.229%	1.128%	0.974%	1.156%	1.122%	1.073%	0.679%	0.752%	0.620%	0.547%	0.559%	0.489%
		0.0672	***0.0885***	*0.1392*	***0.0851***	***0.0883***	*0.1036*	*0.3116*	*0.2421*	*0.3403*	*0.4089*	*0.3768*	*0.4415*

Table 3.7: Momentum test portfolio excess returns assuming value weighting and a single month gap between portfolio estimation and holding period. Each 3 x 3 square within the table represents average momentum excess returns in a percentage form as well as italicized p-values that are emboldened when significant at the 10%, 5% and 1% level

E:H	3	6	9	12
3	1.2962%	0.9431%	0.6640%	0.6808%
	*0.0602***	*0.1362*	*0.3436*	*0.2942*
	[4]	***[0]***	***[0]***	***[0]***
6	1.1870%	1.2579%	1.4819%	0.8710%
	0.0861	*0.0458*	*0.0251*	*0.1670*
	[2]	***[6]***	***[9]***	***[0]***
9	1.1091%	1.1570%	1.1293%	0.8809%
	0.0936	*0.0807*	*0.0833*	*0.1789*
	[0]	***[1]***	***[0]***	***[0]***
12	1.0864%	0.9648%	0.5329%	0.4082%
	0.1078	*0.1657*	*0.4287*	*0.5399*
	[0]	***[0]***	***[0]***	***[0]***

Table 3.8: Average excess returns, p-values and number of significant simulations assuming value weighting and a one month gap between portfolio estimation and holding period. (,**,*** indicating significance at 10%, 5% and 1% level)*

The effect of a single month gap applied to the value weighted momentum excess returns is far more profound when compared to the equally weighted momentum sorts. The average difference between the value weighted 'gapped' and 'no gap' portfolio returns is 0.149% per month and is significantly different from zero at the 5% level. On a pure simulation basis, 66% of the 'gapped' portfolio returns are greater than their 'no gap' counterparts. Considering the effects of variation in the estimation period, the greatest margin of gapped versus no-gap momentum excess returns is experienced assuming an estimation period of three months, where the average difference in excess returns is 0.4% per month. Consistent with the equally weighted results, the 'gapped' excess return decreases as the estimation period extends beyond three months and turns significantly negative under the assumption of an estimation period of twelve months. Similarly, when considering a variation in portfolio holding periods, the most significant outperformance of value weighted 'gapped' simulations is achieved assuming holding periods of three and twelve months.

The results of the value-weighted momentum sorts that allow for a single month between portfolio estimation and investment depict a stronger argument in favor of micro-structure effects, bid-ask bounce and short-term reversal in share prices. The allowance for a single month gap results in value weighted momentum excess returns increasing by 0.149% per month. Furthermore, the positive benefit of applying the one month gap methodology is most apparent in the narrowest estimation and holding period, providing evidence in favor of value-weighted momentum profits being more susceptible to short and long term reversal in share prices. The results further indicate

that the magnitude of the benefit is probably attributable to the effects of value-weighting, caused by over weighting more liquid constituent shares in portfolio sorts, resulting in augmented momentum profits.

The results are therefore twofold. Like Jegadeesh and Titman (1993), irrespective of the weighting methodology applied in portfolio sorts, the application of the methodological variation that allows for a month gap between portfolio estimation and investment increases momentum excess returns by approximately 0.1% per month. Considering the equally weighted momentum test portfolios, the effects of the methodological variation are less pervasive when compared to the value weighted results. A potential and plausible reason for the greater effect experienced in the value weighted sorts relates to increased liquidity and the effects of liquidity on reversal in share prices. Lee and Swaminathan (2000) found that liquidity accelerates reversal, therefore, since value weighted sorts increase the liquidity loading in momentum portfolios, the effect of the one month gap (which is used to remove the effects of extreme short-run reversal) logically should have greater impact on momentum excess returns.

3.5. DO MOMENTUM EXCESS RETURNS EXPERIENCE REVERSAL-ASSUMING PORTFOLIO HOLDING PERIODS IN EXCESS OF TWELVE MONTHS?

Debondt and Thaler (1985, 1989) found that historical winner and loser shares tend to experience reversals over long holding periods where “long” implies holding periods between twelve to sixty months. The presence of momentum and long-term reversal provides evidence in favor of behavioral explanations related to under and overreaction, as the absence of an adequate risk based theory strengthens the plausibility of a behaviorally based explanations of pricing anomalies. The following section extends the analysis of momentum in share prices by considering portfolio holding periods (*H*) of 24, 36, 48 and 60 months in order to determine whether reversal is present in momentum portfolios that are sorted on the cross-section of shares listed on the JSE. For the purposes of empirical consistency, an identical methodology is applied in terms of portfolio formation where simulations are run allowing for variations in liquidity and transaction cost levels assuming overlapping buy-and-hold portfolio returns.

Conrad and Kaul (1993) found that methodological differences significantly impacted the returns attributable to long-term reversal strategies, where the authors suggested the application of buy-and-hold return estimation as cumulative abnormal returns (CAR’s) tend to compound errors attributable to bid-ask bounce and other market frictions. Therefore, the results presented in the following section (indirectly) are more stringent when compared to other studies of reversal in share prices. A further key difference relates to the estimation period (*E*), which does not vary and is assumed to be twelve months throughout each variation in portfolio holding periods. The purpose of limiting the estimation period to twelve months goes beyond tractability, but rather

attempts to utilize empirical consistency as the twelve month window is the only estimation and holding period used by both medium (Jegadeesh and Titman (1993)) and long term studies (Debondt and Thaler (1985)). The purpose of the test is not to determine whether long-term reversal is an investable and viable strategy present on the cross-section of shares listed on the JSE, but rather to determine whether momentum shares on the JSE eventually reverse.

The results of the long-term portfolio simulations are presented in Tables 3.8a and 3.8b below and represent the excess returns earned by the historical loser portfolios over their winner counterparts. As mentioned, shares are classified based on their historical cumulative return measured over the previous twelve estimation window period and sorted into one of five quintile portfolios, where portfolio one represents the historical winner portfolio and portfolio five the historical loser. The time-series excess returns of portfolio five minus one (loser minus winner) are averaged and the associated p-values derived from the paired sample t-tests are presented. Once again, simulations are conducted along equally and value weighted assumptions and allow for variations in liquidity (proxied by a combination of cumulative zero daily trades and turnover) and transaction costs proxies by price.

Table 3.8a presents the test portfolio simulations assuming equal weighting. The results depict that there is significant variation in excess returns as the assumed portfolio holding period increases. The findings are therefore consistent with Debondt and Thaler (1985, 1989) as the excess returns of historical losers over historical winner increases monotonically with the assumed portfolio holding period. Considering the excess average returns achieved assuming a 24 month holding period, the average loser minus winner excess return is -0.5% per month and not significantly different from zero. The implication is that even at holding periods of 24 months, winner portfolios outperform loser portfolios, achieving economically higher returns yet are not significantly different from zero. Moving to a portfolio holding period of 60 months, the average excess return of the loser over winner shares increases to 0.17% on average but is statistically insignificant.

H	24			36			48			60		
	PF1	***PF2***	***PF3***	***PF1***	***PF2***	***PF3***	***PF1***	***PF2***	***PF3***	***PF1***	***PF2***	***PF3***
LF1	-0.8131%	-0.6311%	-0.7030%	-0.3500%	-0.3032%	-0.3862%	0.0285%	-0.0619%	-0.1293%	0.2087%	0.1883%	0.2124%
	0.1160	***0.1982***	***0.1478***	***0.4901***	***0.5340***	***0.4211***	***0.9543***	***0.8977***	***0.7847***	***0.6741***	***0.7304***	***0.7125***
LF2	-0.5910%	-0.5653%	-0.5767%	-0.2344%	-0.2832%	-0.3041%	0.1289%	0.0549%	-0.0011%	0.0292%	0.1256%	0.3755%
	0.2902	***0.2900***	***0.2702***	***0.6700***	***0.5923***	***0.5566***	***0.8124***	***0.9166***	***0.9983***	***0.9513***	***0.8108***	***0.5114***
LF3	-0.3405%	-0.1519%	-0.1724%	-0.1142%	0.0871%	0.0723%	0.1989%	0.3890%	0.3974%	-0.0392%	0.0609%	0.3666%
	0.5627	***0.7948***	***0.7618***	***0.8435***	***0.8797***	***0.8971***	***0.7295***	***0.4971***	***0.4733***	***0.9335***	***0.9051***	***0.5105***

*Table 3.8a: Loser minus winner reversal portfolios assuming equally weighted returns, allowing for variations in holding period (H), liquidity and price filters. P-value are emboldened and directly below the relevant portfolio excess return. Again p-values are assigned asterisks where *, **, *** represents significance at the 10%, 5% and 1% level*

	E	24			36			48			60		
H		***PF1***	***PF2***	***PF3***	***PF1***	***PF2***	***PF3***	***PF1***	***PF2***	***PF3***	***PF1***	***PF2***	***PF3***
12	***LF1***	-0.4641%	-0.3187%	-0.3299%	-0.1970%	-0.1022%	-0.0955%	0.1302%	0.2215%	0.2858%	0.2139%	0.2975%	0.3259%
		0.4412	***0.5891***	***0.5727***	***0.7322***	***0.8570***	***0.8656***	***0.8149***	***0.6851***	***0.6011***	***0.6904***	***0.5742***	***0.5391***
	LF2	-0.3675%	-0.1406%	-0.1968%	-0.1206%	0.0091%	-0.0325%	0.2863%	0.4097%	0.3296%	0.3827%	0.4579%	0.3477%
		0.5462	***0.8155***	***0.7381***	***0.8367***	***0.9875***	***0.9545***	***0.6127***	***0.4656***	***0.5500***	***0.4868***	***0.4017***	***0.5164***
	LF3	-0.2232%	-0.1059%	-0.1588%	-0.0089%	0.0881%	0.0398%	0.3309%	0.4337%	0.3942%	0.4396%	0.4883%	0.4350%
		0.7184	***0.8630***	***0.7951***	***0.9882***	***0.8821***	***0.9463***	***0.5666***	***0.4492***	***0.4921***	***0.4326***	***0.3819***	***0.4374***

*Table 3.8b: Loser minus winner reversal portfolios assuming value weighted returns, allowing for variations in holding period (H), liquidity and price filters. P-value are emboldened and directly below the relevant portfolio excess return. Again p-values are assigned asterisks where *, **, *** represents significance at the 10%, 5% and 1% level.*

The results therefore indicate that momentum profits do experience reversal but only turn negative at holding periods in excess of 36 months. The results further display the effects of transaction costs and liquidity on the reversal experienced in momentum profits. Considering the effects of liquidity first, the reversal portfolios at each holding period seem highly sensitive to the application of a liquidity filter. Considering only the high and low liquidity simulations (LF3 and LF1), the high liquidity reversal portfolios (LF3) exceed their low liquidity counterparts (LF1) by 0.3% per month on average and the difference is significant at the 5% level implying that the higher the level of liquidity, the greater the magnitude of reversal, consistent with the findings of Lee and Swaminathan (2000) and more recently Page, Britten and Auret (2013).

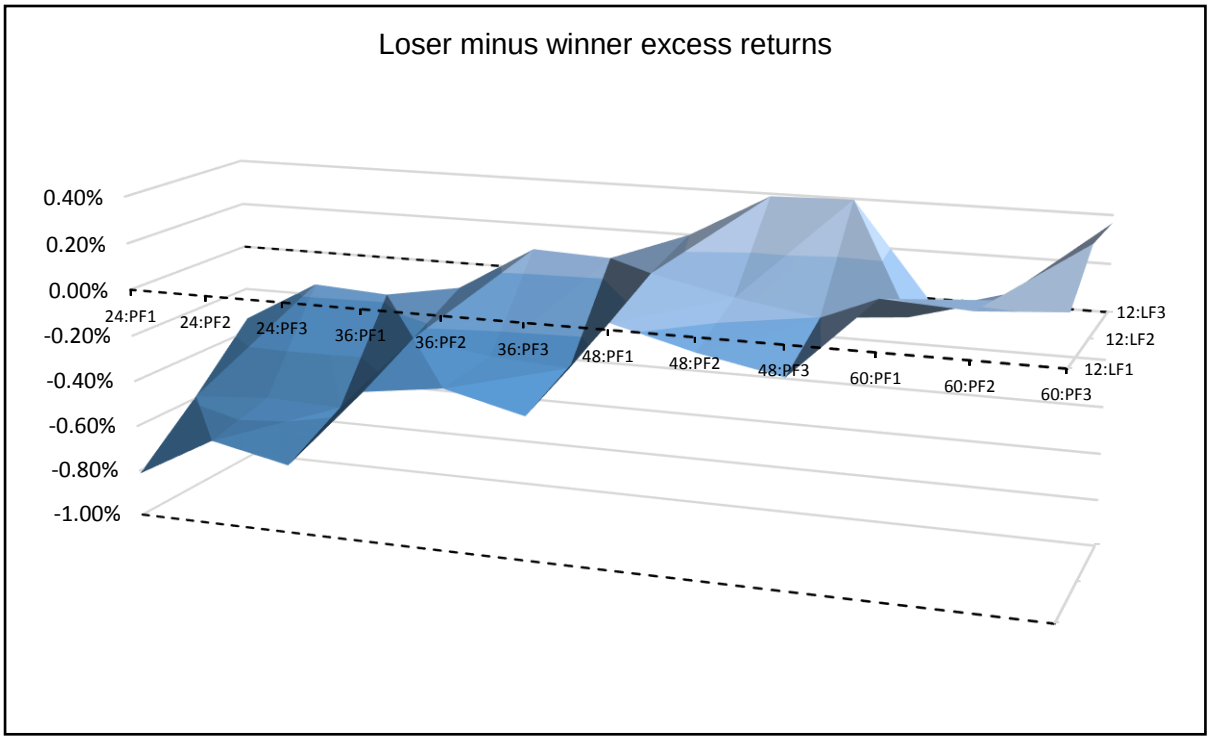
Notably, the sixty month holding period test portfolios failed to exhibit the same relationship (sensitivity) with liquidity as the high liquidity excess returns were not significantly different from their low liquidity counterparts. The results indicate that, unlike the momentum simulations, reversal is more sensitive to the underlying liquidity of constituent shares, especially when using a combination of zero daily trades and turnover as a proxy. Considering the effects of transaction costs on reversal portfolio excess returns, the relationship between reversal excess returns and transaction costs seems to be weakly positive at best. Considering only the extreme transaction cost filter test portfolios (PF3 and PF1), the most stringent filter portfolios (PF3) achieve excess returns that are greater than their less stringent counterparts (PF1) by 0.09% per month on average yet, the difference is not significant. The implication of the results in terms of liquidity and transaction costs is that even though momentum and reversal are methodologically and theoretically related, empirically they respond differently to variations in liquidity and trading costs.

The results of the equally weighted simulations indicate that momentum portfolios do indeed reverse and the magnitude of the reversal tends to increase given the length of the portfolio holding period. Table 3.8b depicts the results of the reversal portfolios assuming value weighted returns. Consistent with the momentum results, the effects of value-weighting seem to decrease momentum profits but simultaneously increase the returns attributable to the extreme loser portfolios. Reversal portfolio profits increase monotonically as the holding period increases, initially achieving negative excess average returns of -0.26% per month but increase to 0.38% per month on average. The difference in results are best described visually where figures 3.4a and 3.4b depict the surface diagrams of the loser minus winner excess returns, allowing for a variation in holding period, liquidity and transaction costs.

Figure 3.4b depicts a distinct slope when allowing for an increase in the portfolio holding period. Value-weighting returns results in portfolio excess returns being 0.2% greater per month than their equally weighted reversal counterparts on average, with the difference being

significant at the 1% level. The results may be a manifestation of the additional liquidity effect of value-weighting where the larger market capitalization, higher liquidity shares receive larger in-portfolio weightings. Consistent with the findings of Lee and Swaminathan (2000) and the momentum sorts above, long-term reversal profits increase under the assumption of value weighting.

Figure 3.4a: Loser minus winner average excess returns assuming equal weighting



Interestingly, the natural liquidity tilt experienced through value weighting does not seem to reduce the effect of the liquidity filter but rather causes the opposite. Considering only the extreme liquidity bands (LF1 and LF3), the difference in average returns between the highest and lowest liquidity reversal portfolios is 0.18% per month and significant at the 1% level. The results are more consistent than those of the equally weighted simulations, as irrespective of holding period or transaction cost filter, the high liquidity simulation excess returns are always greater than their low liquidity counterparts. Once again, like the equally weighted simulations, the effects of transaction costs are less pervasive on the value weighted reversal portfolios. In simulated results, the lowest transaction cost portfolios (PF3) achieve excess returns that are economically greater than the high transaction cost reversal portfolios, but the difference of 0.08% per month is not significantly different from zero. The results of the reversal simulations indicate that momentum portfolios do experience reversal on the cross-section of shares listed on the JSE, and that irrespective of weighting mechanism tend to experience greater levels of

reversal as portfolio holding periods increase. Notably, none of the reversal portfolio excess returns are statistically significant.

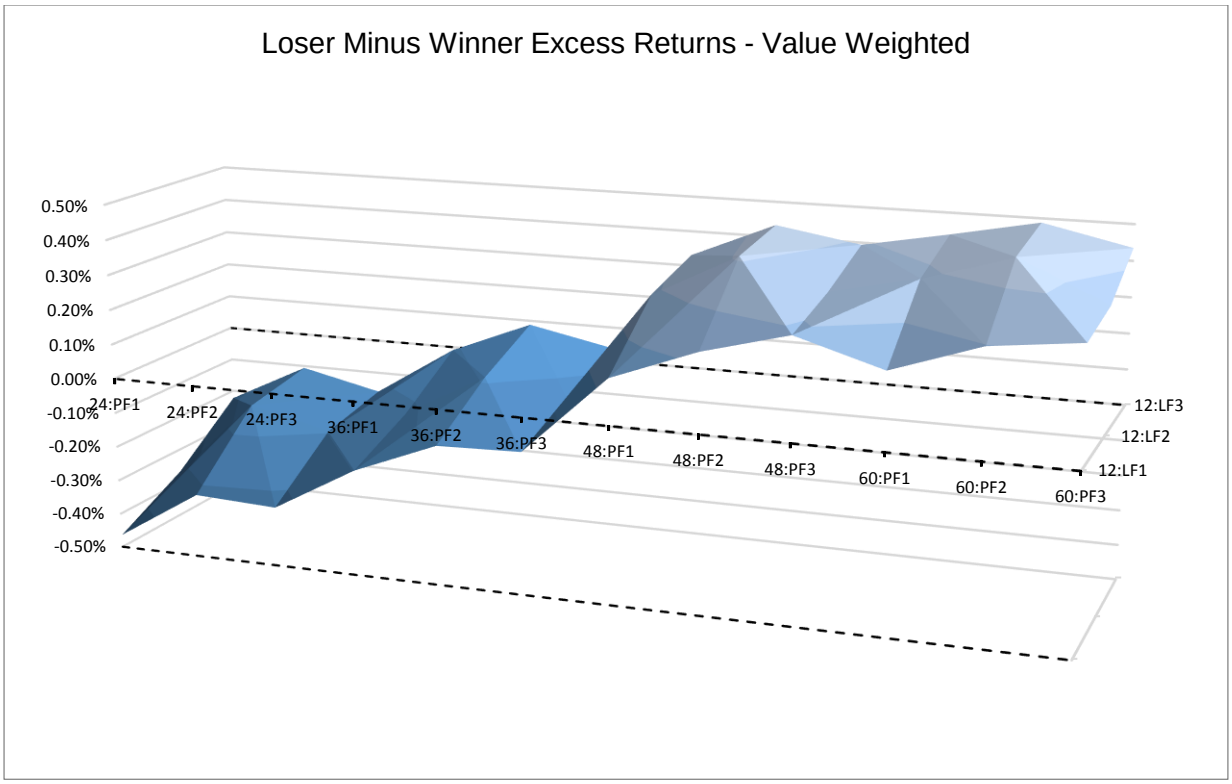


Figure 3.4b: Loser minus winner average excess returns assuming value weighting

The possible reasons behind the lack of significance in reversal results may relate to the fact that only the twelve month portfolios estimation period was used. A further possibility may relate to the methodology applied when calculating returns, specifically buy-and-hold as opposed to the cumulative abnormal return methodology of Debondt and Thaler (1985). Unlike the momentum simulations, the reversal portfolios are far less sensitive to the effects of transaction costs. Such a result may relate to the limits to arbitrage argument, however, logically (and conversely when applied to momentum), the longer the time period of the investment, the greater the opportunity for an investor to absorb the initial transaction cost attributable to the investment.

Consistent with the findings of Lee and Swaminathan (2000) and the momentum results presented above, liquidity seems to maintain a significant relationship with reversal returns. As with the momentum results, the value weighted reversal portfolios experience significantly higher excess returns. Moreover, the high liquidity reversal excess returns are greater than the lower liquidity simulations with the difference being significant at the 1% level, assuming equal and value weighting respectively. To summarize, applying an identical methodology to momentum and reversal portfolios, the results indicate that high momentum shares (previous

winners) do experience continued positive excess returns, however, the return continuation does indeed reverse with both the holding period and liquidity of the underlying constituent shares contributing to the magnitude of the reversal.

3.6. CHAPTER SUMMARY

The results of the chapter indicate that the momentum premium, when measured on a univariate basis, exists and is persistent over the time period January 1992 to June 2015 on the cross-section of shares listed on the JSE. The purpose of the chapter is to define, applying univariate analysis, whether momentum is present, significantly positive, and sensitive to empirical/methodological variations and affected by trading costs and liquidity. The results are unique to the South African literature as they dictate that momentum is highly sensitive to the weighting schematic and allowance for one month gap between portfolio estimation and holding period.

Firstly, equally weighted momentum profits are generally 0.38% and 0.29% per month higher than those that apply value-weighting, assuming no-gap and a gap between portfolio estimation and holding period, consistent with the findings of Basiewicz and Auret (2009). Secondly, consistent with the findings of Jegadeesh and Titman (1993) and Asness (1997), micro-structure effects are present and significant on the JSE as both equal and value weighted momentum profits increased when applying a one month gap between portfolio holding and estimation periods. The results indicate that the effect of allowing for a single month gap has a significantly greater impact on value weighted momentum portfolios, where the single month allowance results in an increase of average excess return of 0.149% per month and is significant at the 5% level, compared to 0.083% achieved assuming equal weighting. The findings are intuitively appealing specifically in terms of the impact of liquidity on reversal, described by Lee and Swaminathan (2000). Value weighting indirectly implies that liquid portfolio constituents are assigned higher initial weightings thereby increasing the propensity for reversal. As describe by the results, the allowance for a single month gap has a greater impact when assuming market capitalization (value) weighting.

The results of the portfolio sorts and sensitivities to direct and indirect trading costs i.e. price and liquidity filters are also unique to the literature. Firstly, trading costs seem to significantly affect momentum profits. Irrespective of weighting schematic or accounting for micro-structure effects through the allowance of a single month gap, momentum profits maintain a significantly negative relationship with trading costs. The results are consistent with the limits to arbitrage theory, where the presence and continuity of momentum may be attributable to the costs associated with engaging in such a strategy. The higher the associated costs, the greater the

inability of arbitrageurs being able to exploit the mispricing. The sensitivity of momentum to the underlying liquidity of portfolio constituents is less apparent, yet the evidence presented is largely consistent with the findings of Lee and Swaminathan (2000) in that higher liquidity tends to result in earlier reversal.

Lastly, the results are consistent with the findings of Debondt and Thaler (1985) and Conrad and Kaul (1993). The final set of tests proved that momentum profits on the JSE eventually do reverse. Once again, the findings are consistent with Lee and Swaminathan (2000) as value weighting, which results in more liquid share being up-weighted, results in greater levels of reversal. However, the results are also consistent with Conrad and Kaul (1993) as long-term reversal is highly sensitive to the portfolio return methodology applied. As described in section 3.2, all portfolio returns are calculated on a buy-and-hold basis where shares are assigned an initial portfolio weighting that free-floats until the next portfolio sorting period. The results of the final tests indicate that momentum profits reverse, yet none of the long-term reversal profits are significantly different from zero. A further interesting finding relates to the shift in portfolio dynamics experienced by the momentum and reversal portfolios. As mentioned, momentum portfolios are distinctly more sensitive to changes underlying transaction costs when compared to liquidity. Interestingly, the dynamic seems to shift when assuming portfolio holding periods in excess of twelve months. At longer portfolio holding periods, variations in liquidity significantly impact portfolio returns, with high liquidity portfolios outperforming their low liquidity counterparts by 0.29% and 0.18% per month on an equally and value weighted basis respectively (and both being significant at the 1% level).

In summary, the evidence presented above is consistent with the local literature per van Rensburg (2001), Muller and Ward (2013) and Page, Britten and Auret (2013) where momentum is found to be a significant and profitable stylistic investment strategy when sorting shares solely on historical cumulative returns. Importantly, the results presented above provide new insights into the momentum premium on the JSE and significantly contribute to the current body of literature in terms of findings related the optimal portfolio estimation and holding period windows, the effects of value and equal weighting, allowing for a single month gap between portfolio estimation and holding periods, the dynamics of momentum returns in relation to the underlying liquidity and trading cost assumptions applied in portfolio sorts and lastly, whether momentum returns on the JSE do eventually reverse over extended portfolio holding periods in excess of twelve months. The results therefore provide a plethora of information to practitioners and academics alike in terms of conducting univariate momentum sorts on the cross-section of shares listed on the JSE. The chapter that follows extends the test to bivariate tests of momentum by considering non-momentum factor premiums. The

purpose of the test is to determine whether momentum is independent of non-momentum factors and further attempt to identify the interaction between momentum and the non-momentum factor premiums sorted on the cross-section of shares listed on the JSE.

CHAPTER FOUR: THE INTERACTION BETWEEN MOMENTUM AND OTHER STYLISTIC INVESTMENT FACTORS

Evidence of momentum in share prices on the JSE was presented in Chapter Three of this study. The portfolio sorting methodology was based solely on share price returns and therefore are considered univariate tests of momentum. In order to further understand and disentangle the momentum premium, the following chapter intends to determine whether momentum in medium term share prices is an independent stylistic anomaly that is persistent even when applied in conjunction with other styles/anomalies that have been documented in both South African and international literature. In order to test interaction and independence, bivariate dual portfolio sorts will be conducted using the six month estimation and holding period momentum in conjunction with pricing anomalies that have been popularised in literature, specifically; size (market capitalization), value (book-to-market ratio), liquidity (proxied by turnover), market beta, idiosyncratic risk and currency risk. Generally, independence and interaction are considered mutually inclusive, however, bivariate tests present an element of mutual exclusivity as described by the null hypotheses that follow.

$$H_{A,0}: Momentum\ is\ not\ \boldsymbol{independent}\ of\ other\ stylistic\ anomalies$$

$$H_{B,0}: There\ is\ no\ significant\ \boldsymbol{interaction}\ between\ Momentum\ and\ other\ stylistic\ anomalies$$

In reference to hypothesis ***A***, independence tests in dual sorts relate to whether momentum is present across portfolio sorts, even when allowing for variation in a seemingly unrelated styles. If the momentum premium is both present and significant within dual sorted portfolios, the implication is that momentum is independent of the unrelated style. Hypothesis ***B***, in reference to interaction, is a secondary test that considers the magnitude and variation of momentum resulting from variations in the unrelated style. If the momentum premium is positively or negatively related to the variation in the other considered style but still remains significant throughout the dual sort simulations, one would fail to reject the independence null hypothesis but reject the interaction null hypothesis. Therefore, beyond independence, the interaction test will provide insight regarding the optimal combination style that results in the greatest gross and risk adjusted profit on the cross-section of shares listed on the JSE.

4.1 DATA AND METHODOLOGY – DUAL SORTING

Two methodologies are to be applied to the dual sorted portfolios, namely independent share by share sorts and dual weighted sorts. The first sorting mechanism is an independent sorting procedure where shares are sorted at each portfolio formation date based on their historical

cumulative six less one month returns and the other style criteria applied (examples of the independent sorting applied in literature are Fama and French (1992, 1993), van Rensburg and Robertson (2003), Basiewicz and Auret (2009), Gilbert, Strugnell and Kruger (2011) and more recently Page and Auret (2014)). Once again, arithmetic buy-and-hold returns are calculated where, at initiation, each share is assigned an initial weighting which is allowed to vary across the portfolio holding period, until the next sorting period where the criteria shares are assigned new weightings. In order to ensure an investable universe, a number of exclusion criteria are applied where shares are screened along cross-sectionally defined liquidity and transaction cost benchmarks.

For the purpose of inclusion within a bi-annual sort, shares require at least twelve months of historical return, a share price greater than 100 cents at portfolio formation, cumulative zero daily trades less than 100 days measured over the previous year and an annual average turnover greater than the cross-sectionally defined bottom 10th percentile at the portfolio sort date. At each portfolio formation date shares are ranked and sorted into one of three terciles using a 33rd / 66th percentile split based historical six minus one cumulative momentum and the respective non-related style. Nine test portfolios are then formed based on tercile ranked shares and portfolios are held for six months. Importantly, each share is assigned an equal weighting at portfolio formation and portfolio returns are calculated on a buy-and-hold basis. If a share delists over the holding period, the share is assigned a -100% return. In order to mitigate any potential calendar effects (i.e. January effect) and beginning and end of sample bias, two portfolio formation start dates are assumed, where the former initiates in January 1992 and the latter in June 1992. The return series are then arithmetically combined in order to define a single time-series of average returns related to the specific dual sorted test portfolio.

A potential issue that may apply to the share-by-share independent dual sorts relates to the relatively limited investable universe of shares listed on the JSE. Compared to International equity indices, the JSE is relatively small and illiquid, with the majority of investable shares being limited to the larger market capitalization stratum. In order to ensure that portfolio constituents of the test portfolios are investable and liquid, as mentioned above, liquidity and price screens are applied at each portfolio sort date. A potential issue that may arise is that the constrained investable universe results in a limited number of portfolio constituents within each of the test portfolios, resulting in portfolios that may contain industry bias, lack diversification and produce monthly returns that are subject to high levels of noise.

Figure 4.1 depicts the various liquidity stratum per the Findata@Wits database over the sample period January 1992 to June 2015. The figure provides insight into the investable

universe of shares by separating the liquidity stratum based on turnover and the number of zero daily trades. The figure indicates that the even though the number of shares listed on the JSE has decreased over the sample period, the JSE seems to be more liquid. The blue portion of the figure indicates the total number of shares listed on the JSE per the Findata database. The orange portion depicts the number of shares per annum that plot above the 20th percentile based on the log of turnover. The grey portion of the figure depicts the proportion of shares that trade at least 75% of the time on average over the previous year. Lastly, the green portion of the figure indicates the combined liquidity filter that considers both turnover and zero daily trades. After applying additional constraints such as price filters in order to proxy trading costs and the required number of historical return data points at each sorting period[5], the investable universe is further limited.

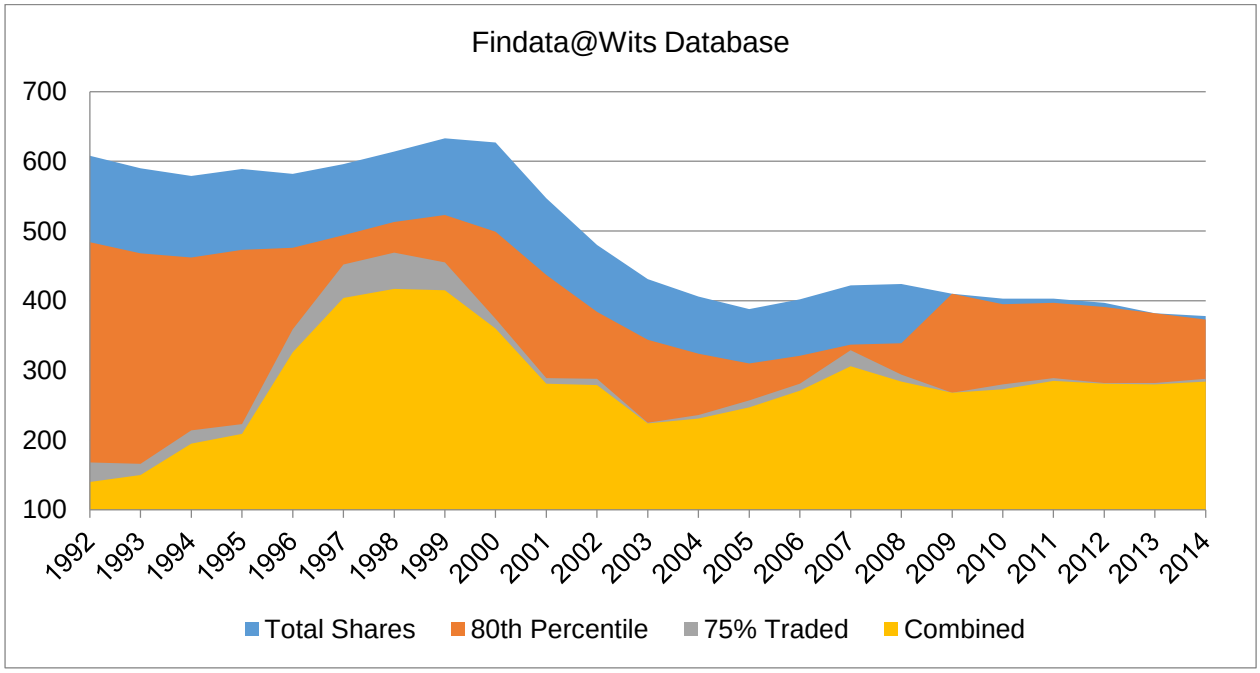


Figure 4.1: Liquidity Stratum per Findata@Wits

The potential noise and "small sample" effect may not necessarily impact the efficacy of results, yet in order to add additional robustness to the bivariate sorting tests, a dependent sorting methodology is applied. The secondary portfolio formation and sorting procedure is inspired by the methodologies of Lo and Mackinlay (1990), Lewellen (2002), Jegadeesh and Titman (2002), McLean (2010) and Asness, Moskowitz and Pedersen (2013) where weighting is applied as an additional dimension to generating returns that mimic factor premiums.

[5] This is in order to ensure that the momentum value for each share is in fact made up of the historical cumulative returns measured over the applied estimation period i.e. using a six month estimation period would require shares to have at least six months of historical returns

The basis of the suggested (and novel) dependent dual sort is 'dependent' in nature as shares are initially sorted on momentum which is applied as the initial share selection criteria. Shares within each momentum portfolio are then weighted based on the secondary factor, in order to create a synthetic exposure to the secondary pricing factor applied within the bivariate sort. The sort is deemed dynamic as the weighting procedure inverts based on the base momentum portfolio. The methodology applied in dual sorts is adapted to consider evidence related to the particular style. As an example, when sorting on momentum and value, initially shares are sorted into quintile portfolios based on their E-1 estimation period cumulative return. Within the upper quintile portfolios (portfolios 1 (extreme winner) and portfolio 2), shares are weighted based on their current book-to-market ratio, thereby giving higher value shares greater initial weights within the extreme winner portfolios. The dynamic aspect of the weighting mechanism entails that the inverse of the book-to-market ratio are applied as initial weights for the extreme loser portfolios (portfolios 4 and 5). The net result is therefore quintile momentum portfolios (sorted initially on momentum) weighted to mimic the value effect based on the book-to-market ratio.

The benefit of the methodology is the allowance for quintile momentum sorts, where each constituent share is weighted using the other style in question. The methodology is largely inspired by the WRSS (relative strength) was first described by Lo and Mackinlay (1990) and was specifically applied to momentum, where shares within momentum deciles were assigned initial weights equal to their historical momentum. The result was a natural long-short portfolio as the highest momentum shares generally produced positive returns and hence where effectively 'long' while loser shares produced negative cumulative returns and therefore received negative weightings (fictitious short position). The results of the dual dependent sort will provide further insight regarding the consistency, independence and interaction of momentum with the unrelated styles considered. A further significant benefit is that the application of the dependent dual dynamic sort is far less susceptible to small sample bias, noise and the impact of outliers when compared to the bivariate independent sorts. The following sections are structured to separately consider momentum and the unrelated styles, where each style will be independently described and tested with momentum in bivariate portfolio sorts.

4.2. BIVARIATE PORTFOLIO SORTS

4.2.1. Momentum and size

The size premium, credited to Banz (1981) was one of the initial pricing anomalies that achieved both attention and notoriety in terms of disproving the notion of efficiency and the

capital asset pricing model. Over the latter half of the 20th century, a consistent and persistent size premium led to Fama and French (1992, 1993 and 1995) incorporating size within a three factor pricing model that proved to be highly successful in describing the cross-sectional variation in share returns and has become a standard portfolio attribution and risk determination tool. Many, if not all momentum studies utilise the size premium as a means of describing the momentum premium. Consistent across most momentum studies, size has failed to explain momentum returns, both in dual sorts and attribution time-series regression tests. Notably, in a number of studies[6], momentum was found to have a negative relationship with size, where smaller market capitalization shares tended to achieve higher momentum profits than their larger counterparts. The current body of literature regarding the size effect and its presence on the cross-section of shares listed on the JSE is relatively consistent, where most studies find a size premium[7]. However, a number of recent studies have found that the size effect has largely dissipated (see Auret and Cline (2011) and Page, Britten and Auret (2016)). The section that follows describes the sorting methodologies applied and results of the bivariate independent and dependent sorts.

4.2.1.1. Independent bivariate sort on size and momentum

In order to determine the effects of size on momentum on the cross-section of shares listed on the JSE, dual momentum sorts are conducted on an independent and dependent basis using the methodologies described above. As noted above, the sample and sample period considered covers all shares listed on the JSE over the period January 1992 to June 2015. In order to mitigate the effects of beginning and end of sample bias, two portfolio start dates are assumed, namely January and June 1992. The final time-series return for each portfolio is an equally weighted combination of the two varying start-date portfolios, implying semi-annual portfolio overlap reminiscent of the methodology applied by Jegadeesh and Titman (1993, 2001).

The independent sorting procedure categorises shares into stratum based on their historical six minus one month cumulative return and the natural logarithm of historical average market capitalization measured over the previous twelve months. Portfolio sorts occur on a six monthly basis, where shares are excluded along transaction cost and liquidity criteria. At each formation date, shares require six months of historical returns data, cumulative zero daily trades measured over the previous year totalling less than 100, average historical turnover in excess of the most recent cross-sectionally measured 10th percentile and a share price in

[6] See Lewellen (2002), Rouwenhorst (1998), Hameed and Kusnadi (2002), Chui, Titman and Wei (2002) and more recently Hoffman (2012)
[7] See van Rensburg and Robertson (2003), Basiewicz and Auret (2009, 2010), Gilbert, Strugnell and Kruger (2011) and Page and Auret (2014).

excess of 100 cents. Shares are then independently classified into one of three portfolios based on their historical momentum and market capitalization using a 33rd / 66th percentile split. Dual independent sorts are then conducted where shares are sorted into one of nine portfolios based on momentum and market capitalization and held for the following six months. The desired result is test portfolios that allow for the determination of portfolio performance when varying one style while holding the other constant. The results of the independent sorts based on the natural logarithm of market capitalization and six month historical momentum are presented in the table below.

	Winner	Medium	Loser	WML
Big	1.4011%	1.2934%	0.6608%	0.7403%
	0.0002* **	**0.0000*** **	**0.0835***	**0.0445****
Medium	1.1098%	1.0140%	0.2240%	0.8859%
	0.0010* **	**0.0011*** **	**0.5283**	**0.0065*** **
Small	1.3902%	1.1347%	0.6435%	0.7467%
	0.0001* **	**0.0002*** **	**0.1470**	**0.0797***
SMB	-0.0109%	-0.1587%	-0.0173%	0.0064%
	0.9746	**0.6018**	**0.9641**	

*Table 4.1: Portfolios sorted on six minus one month momentum and average historical market capitalization measured over the previous twelve months. P-values are assigned asterisks based on statistical significance where *,**,*** indicate significance at the 10%, 5% and 1% level.*

The portfolio results presented above depict the average gross and excess returns of the dual portfolio sorts based on momentum and size. Accompanying each test portfolio average return is a related p-value indicating whether the long only or excess portfolio return is significantly different from zero. The far right hand column depicts the winner minus loser (WML) excess average monthly return while the bottom row depicts the small minus big portfolio (SMB) excess average monthly returns. Consistent with international literature, irrespective of the size (market capitalization) of the momentum portfolio, there is a consistent momentum premium on the cross-section of shares listed on the JSE, achieving excess returns between 0.74% and 0.89% per month on average.

However, the findings above indicate that on the cross-section of shares listed on the JSE, momentum profits do not seem to exhibit a distinct negative relationship with market capitalization or size, contrary to evidence presented in similar studies conducted on various global equity markets. Considering extreme size terciles only, the momentum premium in the

small size stratum is only marginally economically higher than the largest size tercile, achieving an additional seven basis points per month on average, but is statistically less significant. Moreover, when considering long only returns, the large capitalization winner portfolio achieves the highest return of 1.4% per month and is significantly different from zero at the 1% level. The small winner portfolio produces only marginally lower average monthly returns, realizing a monthly gross average return of 1.39% per month and is also significant at the 1% level.

Considering a variation in portfolio size while holding momentum constant (an effective test of the size effect), the small minus big excess returns are all negative and do not exhibit any statistical significance. The results are therefore consistent with the findings of Auret and Cline (2011) and more recently Page, Britten and Auret (2016) as the evidence per the above table indicates that the size premium has largely dissipated on the cross-section of shares listed on the JSE and that the underlying market capitalization of momentum portfolios has little bearing on the momentum profits achieved. Lastly, it deserves mention that the most distinct momentum premium emanates from the middle market capitalization stratum, achieving an excess momentum return of 0.89% per month on average that is significant at the 1% level. The source of the middle market capitalization stratum momentum outperformance is largely attributable to the short position in the loser portfolio, as mid-cap winner shares achieved returns of 1.11% per month while their loser counterparts produced the lowest return of all the simulations portfolios, achieving only 0.224% per month or 2.7% per annum.

4.2.1.2. Dependent dual sorts on size and momentum

In order to corroborate the findings of the independent bivariate sorts on momentum and market capitalization, a modified methodology inspired by Lo and Mackinlay (1999) and popularised by Asness, Moskowitz and Pedersen (2013) is used in order to weight momentum portfolio constituents to gain maximum exposure to the size effect. Shares are initially sorted into one of five quintile portfolios based on their cumulative historical six minus one month returns where portfolios 1 and 5 represent the extreme historical winner and loser test portfolios. Within momentum portfolios 1-3, shares are assigned initial weightings based on the inverse of their natural logarithm of market capitalization. Similarly, Momentum portfolios 3-5 are assigned initial weightings based on the natural logarithm of their latest market capitalization. Mathematically, the dynamic style weighting schematic can be represented by

$$W_i = \left(\frac{1}{MC_i}\middle| P = 1,2,3\right) \qquad (4.1)$$

$$W_i = (MC_i | P = 3,4,5) \qquad (4.2)$$

Where W_i represents the weight of each constituent share within the momentum portfolios and is contingent on the core momentum portfolio P. In order to incorporate the size premium within momentum sorts, the in-portfolio weighting of each constituent share is based on the momentum portfolio P (between portfolios one to five) and the most recent natural log of market capitalization. The in-portfolio weighting expressed in equation 4.1 implies that in portfolios one to three, shares are weighted based on the inverse of the natural logarithm of market capitalization while the latter equation implies that the lower momentum portfolios are weighted according to the natural log of market capitalization. The result is a natural in-portfolio tilt that will mimic the size effect.

Portfolio three is incorporated in both weighting mechanisms and the result is the equally weighted average of both portfolios assuming the inverse and conventional weight. The benefit of the dual dependent sort is largely related to the relatively larger number of shares per momentum quintile portfolio, limiting the potential noise and firm specific risk that accompanies small sample portfolio returns. In order to evaluate the returns achieved via the dependent sort, portfolio returns are reported on a monthly gross basis and monthly net risk basis in terms of their respective portfolio Sharpe and Treynor ratios. The Sharpe ratio is expressed as average portfolio return scaled by portfolio standard deviation and the Treynor ratio as average return scaled by market beta derived via OLS regression over the entire portfolio holding period.

	P1	P2	P3	P4	P5	P1-P5
Mean Return	1.9814%	1.1491%	1.1206%	0.9135%	0.4362%	1.5452%
P-value	***0.0000****	***0.0001****	***0.0002****	***0.0039****	***0.2225***	***0.0000****
Sharpe	0.310	0.243	0.226	0.177	0.074	0.268
Treynor	0.024	0.018	0.015	0.013	0.005	0.403

*Table 4.2: Bivariate dependent sorts on momentum and the natural logarithm of market capitalization. P-values are assigned asterisks based on statistical significance where *,**,*** indicate significance at the 10%, 5% and 1% level. All returns and performance statistics are based on monthly returns and risk measures.*

The results of the bivariate dependent sorts confirm the results of the bivariate independent sorts in terms of the consistency of the momentum premium yet are more consistent with international evidence relating to the negative relationship between momentum and firm size. The results of the quintile sorts are more distinct than those portrayed in the previous section, where momentum profits decrease monotonically when moving from the extreme winner to the extreme loser quintile with the extreme winner inverse size weighted portfolio achieving a significant average return 1.98% per month while the size weighted loser portfolio achieves

an insignificant monthly return of 0.44%. The dynamic size weighted momentum premium is 1.55% per month and significant at the 1% level. In order to evaluate the additional benefit provided by weighting momentum portfolio constituents in order to gain more exposure to the size premium, the excess returns per the bivariate dependent weighting schematic are compared to the pure equally weighted and value weighted momentum excess returns constructed using identical assumptions which are displayed in the tables that follow.

	P1	P2	P3	P4	P5	P1-P5
Mean Return	1.9605%	1.1550%	1.0880%	0.8830%	0.4299%	1.5306%
P-Value	***0.0000****	***0.0001****	***0.0003****	***0.0047****	***0.2251***	***0.0035****
Sharpe	0.311	0.243	0.221	0.173	0.074	0.268
Treynor	0.023	0.017	0.015	0.013	0.006	0.155

*Table 4.2(i): Equivalent Equally Weighted Quintile Portfolio Sorts. P-values are assigned asterisks based on statistical significance where *,**,*** indicate significance at the 10%, 5% and 1% level. All returns and performance statistics are based on monthly returns and risk measures.*

	P1	P2	P3	P4	P5	P1-P5
Mean Return	1.9685%	1.1929%	1.1206%	0.9135%	0.4362%	1.5323%
P-Value	***0.0000****	***0.0001****	***0.0002****	***0.0039****	***0.2225***	***0.0036****
Sharpe	0.312	0.250	0.226	0.177	0.074	0.267
Treynor	0.022	0.017	0.015	0.013	0.005	0.161

*Table 4.2(ii): Equivalent Value Weighted Quintile Portfolio Sorts. P-values are assigned asterisks based on statistical significance where *,**,*** indicate significance at the 10%, 5% and 1% level. All returns and performance statistics are based on monthly returns and risk measures.*

The comparative portfolio results are displayed in the table below.

	Size-Premium Weighted	Equally Weighted	Value-Weighted
Mean Return	1.5452%	1.5306%	1.5323%
P-Value	***0.0000****	***0.0035****	***0.0036****
Sharpe	0.2678	0.2681	0.2670
Treynor	0.4030	0.1546	0.1613

*Table 4.3: Comparison of excess momentum returns based on size-premium weighted, equally weighted and value weighted portfolio returns. P-values are assigned asterisks based on statistical significance where *,**,*** indicate significance at the 10%, 5% and 1% level. All returns and performance statistics are based on monthly returns and risk measures.*

The results presented in Table 4.3 present weak evidence consistent with international literature pertaining to the relationship between momentum and size. The size-premium weighted momentum excess returns are marginally higher than those of the equivalent equally

and value weighted winner minus loser portfolio returns, providing additional return of 17 and 15 basis points per annum over the equally weighted and value weighted momentum premiums respectively. The reported Sharpe and Treynor ratios offers further evidence in favour of momentum profits maintaining a positive relationship with the size premium (and therefore a negative relationship with size) as the Sharpe ratio is equivalent to the equally weighted excess return portfolio and marginally higher than the value weighted excess return portfolio. Considering market risk, the Treynor ratio achieved by the size-premium weighted momentum portfolio is approximately three times larger than that of the equally weighted and value weighted momentum excess return portfolios. The difference in Treynor ratios could be due to the smaller capitalization shares having lower betas than their large counterparts (which achieve a higher weighting in the loser portfolio), implying that the winner portfolio that over weights low market capitalization shares will naturally produce a lower market beta.

The results of the dependent sorts are partially consistent with those of the independent sorts presented above. In terms of consistency, momentum profits are present and are not explained by size in both independent and dependent sorts resulting in the rejection of hypothesis A as the momentum premium is independent of the size premium on the cross-section of shares listed on the JSE. The results are mixed in terms of hypothesis B, as the independent sort failed to reject the null of 'no interaction' while the dependent sort provides weak evidence in favour of interaction. Two possible reasons for the inconsistency may relate to the sensitivity of the size premium to the underlying methodology applied in portfolio sorts and whether the liquidity and transaction cost criteria (price filter) applied in portfolio sorts have a greater impact on the size premium as small capitalization shares are more likely to be low price, low liquidity shares. Ultimately, it is beyond the scope of the study to determine which methodology is more appropriate, however, since the evidence is weak at best in confirming the negative relationship between size and momentum, the natural conclusion drawn is that momentum and size do not seem to significantly interact on the cross-section of shares listed on the JSE.

4.2.2. Momentum and value

The value premium, credited to Basu (1983), dictates that shares with market prices that are trading at a discount to a proxy of accounting value ("value" shares hereafter) achieve returns in excess of shares that trade at a premium to their accounting value ("growth" shares). Like the size effect, the value premium has been proven across various international equity markets with the effect being so prominent that Fama and French (1992, 1993 and 1995) argued in favour of the inclusion of the value premium within a three factor framework. Importantly, the

value premium has been consistently proven to exist on the cross-section of shares listed on the JSE[8]. The interaction between momentum and value has been highly topical within the literature, with Chan, Jegadeesh and Lakonishok (1996) being the first to find that momentum "winner" shares are typically growth shares based on the book-to-market ratio and cash flow-to-price while "loser" shares are typically value shares. The results were further confirmed by Asness (1997) who found that momentum returns loaded negatively on value and conversely, value returns loaded negatively on momentum. Fraser and Page (2000) tested the hypothesis of Asness (1997) on the cross-section of industrial shares listed on the JSE and found that when conducting bivariate sorts, both momentum and value were significantly independent. The authors stated that their results differed to Asness (1997) as the dual combination of both styles did not negatively affect their independent returns.

More recently, Asness, Moskowitz and Pedersen (2013) found that a simple two factor value and momentum based attribution model successfully explains the cross-section of asset returns (thirteen asset classes in total) globally. The basis of the model is directly related to the findings expressed in Asness (1997) in that the value premium emanates from the investment in shares (or assets) trading a discount to their book value. The cause of the discounted value could be attributed to a number of reasons, one of which could certainly be that market participants have recently overreacted to negative news. Conversely, momentum winner shares have recently experienced significant gains, potentially resulting in such shares trading at a premium to their book values. The overall implication is that the two phenomena sit at opposite ends of the investment spectrum and therefore maintain a negative covariance structure through time.

The tests that follow are therefore an extension of those conducted by Fraser and Page (2000), intending to determine the independence and interaction of momentum with the value premium on the cross-section of shares listed on the JSE. Importantly, only the book-to-market ratio is used as the proxy for value as both Auret and Sinclaire (2006) and Basiewicz and Auret (2009) found that the book-to-market ratio is the optimal proxy for value on the JSE. The tests that follow add to the power of the test conducted by Fraser and Page (2000) as the scope of shares considered is increased to encapsulate all shares listed on the JSE as opposed to limiting the universe to Industrials and further focusing on a more recent wide and long dataset of shares.

[8] See van Rensburg and Robertson (2003), Auret and Sinclaire (2006), Basiewicz and Auret (2009), Gilbert, Strugnell and Kruger (2011) and more recently, Page and Auret (2014).

4.2.2.1. Independent bivariate sort on momentum and value

The independent sorting methodology is identical to that applied in the bivariate sorts based on size and momentum. Once again shares are sorted semi-annually, assuming two portfolio initiation dates, January and June 1992. At each sorting period, shares are excluded along liquidity, price impact and transaction cost criteria in the form of turnover (excluded if below the 10th percentile), zero daily trades (limited to 100 zero daily trades over the previous year) and price (below 100 cents). Shares also require at least 12 months of historical return data and non-negative book-to-market ratios. At portfolio formation, shares are sorted independently on their six minus one cumulative return and most recent book-to-market ratio into one of three portfolios based on a 33rd / 66th percentile split. The result is nine test portfolios that are then held for six months post sort after which portfolios are re-sorted. The results of the independent sort based on momentum and value (proxied by the book-to-market ratio) are presented in Table 4.4 that follows. Like Table 4.1, momentum sorts are presented in the columns, value in the rows, momentum excess returns in the far right column and value excess returns in the bottom row. Under each monthly average return is the two-tailed paired sample t-test p-value.

The results of the bivariate independent sorts on momentum and value indicate that, consistent with the findings of Asness (1997), momentum and value are not independent on the cross-section of shares listed on the JSE. Indeed when considering long-only returns, irrespective of momentum (value) stratum, winner (value) shares outperform loser (growth) shares. However, when considering the significance of excess returns, the high value momentum premium is only 0.416% per month, equating to 4.997% per annum but fails to achieve any form of significance. The results of the high value momentum portfolios provides evidence consistent with the literature in respect of the value phenomenon. Considering the long-only test portfolios, the high value winner portfolio achieves a return of 1.478% per month, equating to 17.74% per annum on average and is significant at the 1% level. At face-value, the result indicates that there is a powerful positive interaction between momentum and value. However, when considering the extreme loser portfolio, a different picture emerges. The long-only value extreme loser portfolio achieves a gross monthly return of 1.062%, equivalent to 12.74% per annum on average and is also significant at the 1% level. The result therefore indicates that the superior performance of the high value extreme loser portfolio results in the insignificant momentum excess return.

The implication of the finding is that the prevalence of the value premium results in making the momentum premium redundant in the highest value stratum. Considering the medium and low

book-to-market (growth) momentum sorts, the momentum premium increases monotonically, with the medium and growth stratum momentum premium achieving 1.083% and 1.402% per month, both of which are significant at the 1% level. The results therefore indicate that momentum maintains a negative relationship with the value premium, to the extent that the momentum premium is only statistically significant (profitable) in the medium and growth book-to-market stratum on the JSE.

	Winner	Medium	Loser	WML
Value	1.4781%	1.2769%	1.0616%	0.4165%
	0.0001* **	**0.0001*** **	**0.0095*** **	**0.2746**
Medium	1.3469%	1.3385%	0.2637%	1.0832%
	0.0000* **	**0.0000*** **	**0.4403**	**0.0003*** **
Growth	1.2839%	0.9397%	-0.1185%	1.4024%
	0.0004* **	**0.0033*** **	**0.7504**	**0.0001*** **
VMG	0.1942%	0.3372%	1.1801%	
	0.5590	**0.2470**	**0.0000*** **	

*Table 4.4: Portfolios sorted on six minus one month cumulative momentum and t_{-1} book-to-market ratio. P-values are assigned asterisks based on statistical significance where *,**,*** indicate significance at the 10%, 5% and 1% level.*

Interestingly, when considering the long-only winner portfolios, the gross monthly return decreases as the book-to-market stratum moves from value to growth, indicating that long-only momentum maintains a positive relationship with the book-to-market ratio, yet on a factor premium level, momentum seems to maintain a negative relationship with value. Similarly, the value excess returns indicate that value maintains a negative relationship with momentum, as the value premium decreases when moving through the momentum strata. The winner value premium amounts to 0.194% per month, equivalent to 2.3% per annum on average while the loser value premium is 1.18% per month, equating to 14.16% per annum and is significant at the 1% level.

The difference in momentum premiums between the growth and value momentum excess returns, 1.402% and 0.416% respectively, amounts to 0.986% per month and is significant at the 5% level. An identical test was conducted on the value premium by comparing the loser value premium to that of the winner. The difference in premia is 1.02% per month and is significantly different from zero at the 1% level.

The results of the bivariate independent sort are therefore consistent with the findings of Chan, Jegadeesh and Lakonishok (1996), Asness (1997) and Asness, Moskowitz and Pedersen (2013). Momentum and value are not independent as both premiums are effectively negated

in both the extreme stratum. The momentum premium is reduced to insignificance in the highest value stratum as is the value premium in the highest momentum stratum. The implication of the findings is that both momentum and value are present on the cross-section of shares listed on the JSE and are significant in their long-only forms, where winner portfolios are significantly positive irrespective of the value stratum and similarly, value portfolio returns are positive irrespective of the momentum stratum. However, on a premium level, the results indicate a negative interaction. In fact, the interaction is so extreme that it actually negates the general expected premium emanating from both strategies. Table 4.4 clearly indicates that in the bottom row, the value premium is only significantly positive in loser tercile, achieving an excess return of 1.1801% compared to the winner tercile value premium of 0.1942%. Similarly, the momentum premium per the last column of table 4.4 indicates that the momentum premium is highest in the growth tercile, achieving an excess momentum return of 1.4024% compared to 0.4156% achieved in the value tercile.

The source of underperformance relates to the short position in both the loser and growth portfolios. In terms of both strategies, the high value loser portfolio and the winner growth portfolio both produces significantly positive gross returns. The findings therefore conform to those of Asness (1997) as high momentum growth shares and loser value shares perform extremely well and therefore reduce the respective premia. Furthermore, the results are highly consistent with Asness *et al.* (2013), as the bivariate independent sort depicts a significantly negative relationship between momentum and value, implying a consistently negative covariance structure between the respective premia. However, when considering long only portfolio returns, the high value winner portfolio achieves the highest average return, implying that on a long only basis, the findings are consistent with Fraser and Page (2000) as high book-to-market winners produce greater levels of return when compared to their medium and low book-to-market counterparts. The result therefore implies a (long only) positive interaction between value and momentum.

4.2.2.2. Dependent dual sorts on value and momentum

In order to add a further dimension to the test of independence and interaction between momentum and value, the dependent dynamic style weighting methodology is applied where momentum is the core portfolio and the book-to-market ratio is the dynamic weighting metric. Shares are initially sorted into one of five quintile portfolios based on their historical cumulative six minus one momentum return and held for the following six months. Each constituent share is assigned an initial in-portfolio weight based on their most recent book-to-market ratio. In order to capture a similar effect seen in independent sorts, the weighting mechanism varies

based on the specific momentum portfolio. In the higher momentum (winner) portfolios, shares are assigned portfolio weightings equivalent to their book-to-market ratios, resulting in a natural weighting towards value shares within the upper-momentum portfolios. As momentum portfolios tend toward loser shares from portfolio one to five, the weighting mechanism inverts, implying shares are assigned weightings equivalent to the inverse of their book-to-market ratios i.e. weighted based on the price-to-book ratio. The intended result is that the lower momentum (loser) shares receive in-portfolio weightings that result in loser portfolios having a greater growth tilt. The dynamic weighting mechanism is expressed mathematically as

$$W_i = (BM_i | P = 1,2,3) \qquad (4.3)$$

$$W_i = \left(\frac{1}{BM_i} \middle| P = 3,4,5\right) \qquad (4.4)$$

Where W_i is the initial weighting of constituent share i within the momentum portfolio. The weighting of each constituent share is equal to that shares book-to-market ratio (BM_i) contingent on the momentum portfolio P being portfolios one to three. Similarly, if the momentum portfolio is beyond or equal to three, momentum shares are assigned initial weights equivalent to the inverse of their book-to-market ratio. The results of the dependent bivariate value momentum dynamic weighting sort are presented below.

	P1	P2	P3	P4	P5	P1-P5
Mean Return	1.7609%	1.2549%	0.8412%	0.4615%	0.3835%	1.3774%
P-value	***0.0000******	***0.0001******	***0.0168****	***0.2195***	***0.4247***	***0.0318****
Sharpe	0.253	0.246	0.146	0.075	0.049	0.163
Treynor	0.022	0.020	0.012	0.007	0.005	-0.35

*Table 4.5: Bivariate dependent sorts on momentum and the book-to-market ratio. . P-values are assigned asterisks based on statistical significance where *,**,*** indicate significance at the 10%, 5% and 1% level. All returns and performance statistics are based on monthly returns and risk measures.*

The results of the dependent dynamic weighting sort indicate that the momentum premium is independent of the weighting mechanism applied as portfolio returns decrease monotonically when moving from extreme winner to extreme loser portfolios. The extreme winner portfolio achieves a monthly average gross return of 1.76% per month which is significant at the 1% level. The loser portfolio achieves an insignificant gross return of 0.38% per month. The excess momentum return amounts to 1.38% per month, equivalent to 16.52% per annum and is significantly different from zero at the 5% level.

The table further depicts the Sharpe and Treynor ratios of the momentum portfolios, indicating that both risk adjustments prove that winner portfolios outperform their loser counterparts on

a relative risk-adjusted basis, as the Sharpe ratio indicates that the extreme winner produced 25.3 basis points of return per 1% of standard deviation compared to 4.9 basis points achieved by the loser portfolio. At face value, the results indicate that, contrary to the findings of the independent sort, momentum and value are independent as the dynamic weighted book-to-market momentum sort produces a significant excess return premium. Similarly, the results of the Treynor ratio indicate that on a relative market risk adjustment, the extreme winner portfolio achieves 2.2% return per month at an assumed beta equal to the market (beta equal to one), while the loser portfolio achieves a return of 0.5%.

In order to gain further clarity regarding the independence and interaction between momentum and value, the dynamically weighted portfolio excess returns are compared to premia estimated using simple equal and value weighting of constituent shares. The purpose of the comparison allows for the determination of whether the dynamic weighting results in a positive or negative interaction between momentum and the weighting style when compared to non-dynamically weighted momentum returns. If the dependent dynamically weighted momentum portfolios achieve excess returns greater than their equally and value weighted counterparts, then one can conclude that the interaction between momentum and the weighting style is positive, while the inverse would prove that the interaction is negative. The comparative results are displayed in the table that follows.

	Value Premium Weighted	Equally weighted	Value Weighted
Mean Return	1.3774%	1.5306%	1.5323%
P-value	***0.0318****	***0.0035*****	***0.0036*****
Sharpe	0.163	0.268	0.267
Treynor	-0.350	0.155	0.161

*Table 4.6: Comparison of excess momentum returns based on value-premium weighted, equally weighted and value weighted portfolio returns. P-values are assigned asterisks based on statistical significance where *,**,*** indicate significance at the 10%, 5% and 1% level. All returns and performance statistics are based on monthly returns and risk measures.*

The results presented in Table 4.6 confirm the independent sort results presented in the previous section as both the equally and value weighted average excess returns are greater than the premium produced by the dynamic book-to-market weighted momentum long-short portfolio. The equally weighted and value weighted momentum premium is 0.153% and 0.155% greater per month (on average) than the value-premium weighted momentum excess returns, translating into relative underperformance of -1.84% and -1.86% per annum, yet the difference is not statistically significant. Interestingly, when decomposing the source of the underperformance, the long winner position seems more responsible than counter short

(loser) position, which is an opposite result when compared to the bivariate independent results. The bivariate independent tests indicated that the momentum premium in the highest book-to-market tercile was reduced by the short position in the loser high book-to-market portfolio.

Comparing the portfolio 5 (loser) average returns of the different weighting schematics, the dynamic book-to-market weighted momentum achieved an average return of 0.38% per month per table 4.5 while the equally and value weighted loser portfolios achieved average monthly returns of 0.43% and 0.44% respectively (per tables 4.2(i) and 4.2(ii)), implying that the short position of the dynamic book-to-market weighted momentum loser portfolio would produce relatively more favourable results, assuming equivalent winner portfolio average gross returns. The source of the underperformance emanates from the long position, where the long winner equal and value weighted portfolios achieved 1.96% and 1.97% per month on average respectively, while the dynamic book-to-market weighted winner achieved and average gross-return of 1.76%, underperforming the former strategies by 2.4% and 2.5% per annum on average. The implication of the results favour the findings of Chan, Jegadeesh and Lakonishok (1996) and Asness (1997) as the negative covariance structure between value and momentum (as seen in the independent sorts) seems to negatively affect the momentum premium, resulting in a muted momentum effect. This can be further seen when comparing the Sharpe ratios of the excess momentum premia, where the dependent value-momentum premium only provides 16 basis points per standard deviation, almost half that achieved by the equally and value weighted momentum premiums respectively.

Additionally, the Treynor ratios provide evidence in favour of the findings of Asness *et al.* (2013). The negative Treynor ratio for the dynamic book-to-market weighted excess return series is as a result of the series having a negative market factor loading or CAPM beta. The cause of the negative beta could be directly related to the negative covariance structure between value and momentum as the dynamic book-to-market weighted excess return series is constructed to load on both factors. Asness *et al.* (2013) found that a generalised attribution model that solely uses value and momentum factor premiums is able to explain a large proportion of the cross-sectional variation in returns across asset classes. By implication, the negative market beta achieved by the excess return series of the dynamic book-to-market weighted momentum portfolio further confirms the negative covariate structure that is largely independent of the market. In conclusion, the results of the bivariate dependent sort provide evidence in favour of momentum not being independent of value on the cross-section of shares listed on the JSE.

Considering the interaction between momentum and value, both the independent and dependent sorts proved that there is a distinct negative interaction between momentum and value as both sorting mechanisms resulted in the momentum premium reduced across the cross-section of shares listed on the JSE. In a risk based framework, the negative covariance structure would provide benefit in explaining the variation returns as independent and inverse return drivers are optimal for a pricing model. In a pure investment framework, the results dictate that a combination strategy that involves momentum and value would be sub-optimal on a pure profit basis but highly beneficial in terms of diversification.

4.2.3. Momentum and liquidity

A number of studies have considered the effects liquidity on momentum profits. Chapter Three of this study found that the application of a liquidity filter produced results consistent with those of Lee and Swaminathan (2000) as more liquid winner and loser shares tended to reverse at a faster rate when compared to their less liquid counterparts. The vast majority of literature has considered liquidity more as an explanatory variable that provides insight into the cross sectional variation in share returns as opposed to an investment style. Amihud and Mendelson (1986) found that low liquidity shares outperform high liquidity shares and more recently Chen, Ibbotson and Hu (2010) found that low liquidity shares, sorted on average turnover, achieve returns in excess of their high liquidity counterparts.

Liquidity and Momentum was initially explored by Lee and Swaminathan (2000) where the study found that the momentum premium was positively related to liquidity, implying results inconsistent with the general (il)liquidity premium evidence. Sadka (2006) found that liquidity was able to explain approximately 60% of the momentum premium in US shares. Hameed and Kusnadi (2002) found that liquidity and momentum maintained a positive relationship across emerging equity markets within the Asia Pacific basin over the period January 1979 to December 1994.

Chan, Hameed and Tong (2000) found that momentum maintained a positive relationship with lagged trading volume, implying a positive relationship between momentum and liquidity. More recently, Page, Britten and Auret (2013) considered the interaction between momentum and liquidity on the JSE over the period January 1995 to December 2010. Consistent with a number of international studies, the authors found that momentum maintains a positive relationship with volume, consistent with the herding behavior.

Importantly, a number of studies that consider liquidity and momentum have found an inverse relationship between the factors. Demir, Muthuswamy and Walter (2004) found that

momentum on the Australian Stock Exchange maintained a negative relationship with average daily trading volume. Pastor and Stambaugh (2003) found a significant and persistent liquidity factor on a cross section of US shares and that the liquidity factor, which was constructed as a fictitious long-short position in illiquid and liquid shares, explained more than half of the momentum premium generated over the sample period. The dynamics of momentum and liquidity are of importance as liquidity is required to drive momentum, specifically when considering behavioral explanations of momentum.

The liquidity premium is generally expressed as the additional return required in order to compensate for liquidity risk. From a risk-based perspective, the expected relationship between momentum and liquidity should be inverse, in that the momentum premium could be partially explained by liquidity risk. Conversely, a positive relationship between momentum and liquidity implies that momentum is to some extent driven by liquidity, which fits neatly in a behaviorally based framework. Momentum has been linked to the under/overreaction hypothesis, where herding is largely responsible for the increased serial-correlation in asset returns that results in both momentum and long-term reversal. Liquidity can be considered both a cause and result of overreaction, as described in Page, Britten and Auret (2013) where the authors conjectured that the liquidity/momentum relationship can be defined as an interrelated system, where positive news increases an assets return, which will drive up the value of the asset which in-turn will result in greater "herding" into the asset, resulting in greater liquidity.

The tests that follow will attempt to define the relationship between momentum and liquidity, effectively replicating the study of Page, Britten and Auret (2013). There are a number of subtle differences in methodology that require mention. Firstly, the authors assumed a twelve month estimation and holding period sort without the allowance for a month between portfolio estimation and sorting. Secondly, portfolio returns were calculated using cross-sectional and time-series arithmetic averages and lastly, volume was used as the proxy for liquidity. The tests to be conducted can be considered methodologically superior, specifically in terms of the calculation of portfolio returns which are calculated on a buy-and-hold basis, various initial liquidity and trading cost filters are applied and most importantly, the turnover ratio is used, which has been found to be a superior liquidity proxy as volume alone tends to be significantly related to market capitalization[9].

[9] See Amihud and Mendelson (1986), Haugen and Baker (1996), Datar, Naik and Radcliffe (1998) and Ibbotson *et al.* (2013)

4.2.3.1. Independent bivariate sorts on momentum and liquidity

Once again, shares are sorted semi-annually into tercile portfolios based on momentum, proxied by their six minus one month cumulative return, and liquidity, proxied by average turnover (monthly volume scaled by the number of shares in issue) measured over the previous year. At each portfolio sorting date, shares are filtered based on liquidity and transaction cost criteria, where shares that have more than 100 zero daily trades over the previous twelve months, a turnover ratio in the bottom tenth percentile and a share price less than 100 cents are excluded.

Shares are simultaneously ranked into three independent stratum based on momentum and liquidity assuming a 33rd /66th percentile split. Shares are therefore assigned to one of nine momentum-liquidity portfolios and held for the next six months until the next sorting period. In order to remove the effects of beginning and end of sample bias, two initial portfolio start dates are assumed, January and June 1992. The dual start date test portfolio time-series returns are then combined on an equally weighted basis. The result is nine test portfolios that allow for the independent variation in momentum (liquidity) while holding liquidity (momentum) constant. The results of the independent portfolio sorts are presented in the table that follows.

	Winner	Medium	Loser	WML
High	1.4948%	1.3629%	0.7264%	0.7684%
	0.0001***	***0.0000******	***0.1079***	***0.0504****
Medium	1.2715%	1.1657%	0.4834%	0.7881%
	0.00015***	***0.00009******	***0.18784***	***0.01388****
Low	1.3515%	1.0509%	0.1164%	1.2351%
	0.0000***	***0.0001******	***0.7211***	***0.0002******
VMG	0.1433%	0.3121%	0.6100%	
	0.60374	***0.21699***	***0.05938****	

*Table 4.7: Portfolios sorted on six minus one month cumulative momentum and average turnover measured over the previous year. P-values are assigned asterisks based on statistical significance where *,**,*** indicate significance at the 10%, 5% and 1% level. All returns and performance statistics are based on monthly returns and risk measures.*

Table 4.7 above indicates that the momentum premium is present across the liquidity stratum, ranging from 0.77% per month, achieved by the high turnover momentum sort to 1.24% achieved by low turnover momentum sort, therefore indicating that momentum and liquidity are largely independent. Allowing for a variation in turnover in order to determine interaction, the momentum premium seems to maintain a negative relationship with turnover as the momentum premium increases monotonically as liquidity decreases. Focusing on the long-

only portfolios, there is barely any variation in the winner portfolio results when allowing for changes in turnover. The high momentum winner portfolio achieves a gross average monthly return of 1.495% that is significantly different from zero at the 1% level. Similarly, the low turnover winner portfolio achieves a gross average monthly return of 1.35% per month and is also significant at the 1% level. The difference in the long only returns between the high and low turnover winner portfolios is an insignificant 0.143% per month.

Significant variation in gross monthly average returns emerges when focusing on the extreme loser stratum. The high turnover loser portfolio achieves a gross monthly average return of 0.726% per month, which just misses significance at the 10% level. The low turnover momentum portfolio achieves the lowest monthly average return, earning just 0.12% per month on average. The difference between the high and low liquidity loser portfolios is 0.61% per month and significant at the 10% level.

The results therefore imply that the magnitude of the low-turnover momentum excess return is largely driven by the short position in the low turnover loser portfolio. The results are largely inconsistent with those of Lee and Swaminathan (2000) and marginally so when compared to those of Page, Britten and Auret (2013). The results indicate that the momentum premium tends to have a negative relationship with liquidity, as the low liquidity momentum premium exceeds the high liquidity momentum premium by 0.47% per month, equivalent to 5.6% per annum. Furthermore, when delving into the source of the outperformance, a result contrary to that of Lee and Swaminathan (2000) emerges as the low liquidity loser portfolio achieves the lowest return of all the tests portfolios.

The most distinctive difference in returns based on liquidity is experienced in the loser portfolios. The high liquidity losers achieve superior returns when compared with their low liquidity counterparts, with the difference in returns being 0.61% per month, equivalent to 7.32% per annum. Additionally, the dual sort on momentum and liquidity produces results that are inconsistent with the liquidity premium. Irrespective of the momentum stratum, high liquidity shares seem to outperform low liquidity shares. The results therefore imply that at best, the momentum premium maintains a negative relationship with liquidity, however, the result is largely driven by the short position in the low liquidity loser portfolios. The same conclusion cannot apply to the application of long only momentum strategies as the high liquidity winner portfolio produces marginally higher returns than its low liquidity counterparts (14.3 basis points per month or 1.72% per annum), but the difference is not statistically significant and therefore only marginally consistent with the results of Page, Britten and Auret (2013).

4.2.3.2. Dependent bivariate sorts on momentum and liquidity

In order to confirm the results of the independent sorts, dependent sorts are implemented where shares are initially sorted into quintile test portfolios based on historical momentum measured over the prior six months, skipping the most recent month in order to mitigate bid-ask biases and other micro-structure effects. Shares are then assigned in-portfolio weights using a dynamic process that mimics the effects of the style based weighting mechanism. Shares are therefore weighted based on their historical average turnover ratio measured over the previous twelve months. In order to mimic the effects of the liquidity premium, the higher quintile portfolios are weighted using the inverse of turnover while the lower quintile portfolios are weighted using turnover. The intended result is that winner portfolios will naturally up-weight lower liquidity constituent shares and similarly, loser portfolios will tilt towards the higher liquidity constituent shares. More formally, the dynamic weighting methodology can be described mathematically as

$$W_{i,1} = \left(\frac{1}{TO_i} \middle| P = 1,2,3\right) \qquad (4.5)$$

$$W_{i,1} = (TO_i | P = 3,4,5) \qquad (4.6)$$

Where W_i represents the in-portfolio constituent share initial weight, TO_i the relative turnover of share i and P, the specific momentum quintile portfolio. The dependent tests of liquidity and momentum would be biased to only consider the liquidity premium if only a single dependent sort was conducted as numerous studies have found a positive relationship between momentum and liquidity (as described above), therefore a second set of simulations are conducted that invert the initial weighting mechanism. More formally,

$$W_{i,2} = (TO_i | P = 1,2,3) \qquad (4.7)$$

$$W_{i,2} = \left(\frac{1}{TO_i} \middle| P = 3,4,5\right) \qquad (4.8)$$

The weighting mechanisms per equations 4.7 and 4.8 express the difference in liquidity weighting where the second weighting mechanism effectively up-weights winner shares that are more liquid and similarly up-weights less liquid loser shares. The reason for shift in methodology when compared to the dual sorts on size and value relates to the divergent evidence relating to momentum and liquidity, where a number of studies find a positive interaction while others find that liquidity partially explains momentum. The results of the dependent sorts are presented in Tables 4.8 and 4.9 below.

	P1	P2	P3	P4	P5	P1-P5
Mean Return	2.0675%	1.1244%	1.2736%	0.7417%	0.2922%	1.7752%
P-value	***0.0000******	***0.0002******	***0.0001******	***0.0307****	***0.4640***	***0.0014******
Sharpe	0.330	0.226	0.237	0.132	0.045	0.266
Treynor	0.027	0.018	0.016	0.010	0.003	-0.204

*Table 4.8: Bivariate dependent portfolio sorts on momentum and liquidity (per equations 4.5 and 4.6). P-values are assigned asterisks based on statistical significance where *,**,*** indicate significance at the 10%, 5% and 1% level. All returns and performance statistics are based on monthly returns and risk measures.*

The dependent sort results depicted in the table above are thus far consistent with those of the independent sorts. The highest momentum portfolio produces gross average returns of 2.07% per month on average and is significant at the 1% level. Portfolio returns to decline monotonically barring the portfolio three (P3), decreasing to 0.29% per month on average achieved by the loser portfolio (P5). The excess momentum return per the first dynamic weighting mechanism is 1.78% per month and significant at the 1% level. Both the Sharpe and Treynor ratios confirm the gross return results as they also decrease monotonically when moving from the winner (P1) to loser (P5) portfolio.

	P1	P2	P3	P4	P5	P1-P5
Mean Return	1.9598%	1.0319%	0.8675%	0.9396%	0.5084%	1.4514%
P-value	***0.0000******	***0.0013******	***0.0044******	***0.0024******	***0.1490***	***0.0106****
Sharpe	0.269	0.198	0.175	0.186	0.088	0.221
Treynor	0.020	0.014	0.013	0.016	0.007	0.055

*Table 4.9: Bivariate dependent portfolio sorts on momentum and liquidity (per equations 4.7 and 4.8). P-values are assigned asterisks based on statistical significance where *,**,*** indicate significance at the 10%, 5% and 1% level. All returns and performance statistics are based on monthly returns and risk measures.*

The results of the secondary dynamic sort are inconsistent with the independent sorts presented above. Firstly, the long only winner portfolio achieves a gross average return of 1.96% per month and is significant at the 1% level. Portfolio returns decrease monotonically when moving from portfolio one to portfolio five, barring the return achieved by portfolio four. The excess return premium is 1.45% per month and is significant at the 5% level. The results therefore indicate that the weighting mechanism seems to have little effect on winner long-only portfolio return as the average returns, whether weighting based on turnover or the inverse of turnover are economically and statistically similar. However, the effects of weighting are more distinguishable in the loser portfolio returns. When weighting the loser portfolio (P5) based on turnover, the average return achieved is 0.29% while the average return achieved when weighting according to the inverse of turnover is 0.51%. The results therefore imply that

like the independent sorts, the large proportion of the difference in excess returns is not related to the long winner portfolio returns but rather those of the loser portfolios. The initial dynamic weighting mechanism up-weights liquid losers but produces a lower return than the second dynamic weighting mechanism that up-weights illiquid losers.

On closer inspection, the results of the bivariate dependent dynamic sorts are not completely at odds with Lee and Swaminathan (2000). The first dynamic weighting mechanism produces effects that are similar to Lee and Swaminathan (2000) as illiquid losers outperform illiquid winners. Additionally, the two simulations mimic the early and late-stage strategies of Lee and Swaminathan (2000). The authors found that price reversals were more pronounced among low liquidity losers and high liquidity winners (early stage) while momentum was more pronounced among high liquidity losers and low liquidity winners (late stage). The consistency of results reflects in the fact that the second weighting mechanism is in effect a late stage strategy while the first mechanism is an early stage strategy and like Lee and Swaminathan (2000), the later stage strategy outperforms the early strategy when conducting momentum sorts. Importantly, the first dynamic weighting mechanism is the only evidence in favour of the conventional liquidity premium, as low liquidity winner shares exceed high liquidity losers by a higher margin than the inverse weighting mechanism. As with the other dependent sorts, the dynamic weighting portfolio results are compared to the equivalent equally weighted and market capitalization weighted quintile sorted momentum excess returns. The results are presented in Table 4.10 below.

	Illiquidity Premium Weighted	Liquidity Premium Weighted	Equally weighted	Value Weighted
Mean Return	1.7752%	1.4514%	1.5306%	1.5323%
P-value	***0.0014******	***0.0106****	***0.0035******	***0.0036******
Sharpe	0.266	0.221	0.268	0.267
Treynor	-0.204	0.055	0.155	0.161

*Table 4.10: Dynamically weighted liquidity versus equally and market capitalization weighted momentum premiums. P-values are assigned asterisks based on statistical significance where *,**,*** indicate significance at the 10%, 5% and 1% level. All returns and performance statistics are based on monthly returns and risk measures.*

The results above further indicate that momentum seems to maintain a negative relationship (and therefore interaction) with liquidity as the dynamic weighting strategy that mimics the conventional liquidity premium (where illiquid shares outperform their liquid counterparts) achieves excess momentum returns that are greater than both the equivalent equally weighted and market capitalization weighted momentum sorts. Moreover, the inverse liquidity premium

weighted momentum excess return underperforms both the equally weighted and market capitalization weighted momentum premiums per tables 4.2(i) and 4.2(ii). In terms of actual outperformance, the liquidity premium weighted momentum portfolio excess returns achieve 25 and 24 basis points per month on average over the equally and value weighted momentum excess returns, equating to an additional 2.93% and 2.92% per annum. Conversely, the inverse liquidity premium weighted momentum returns underperform the same portfolios by 7 and 8 basis points per month, equating to 0.95% and 0.96% per annum.

In conclusion, the results of the bivariate sorts of momentum and liquidity, proxied by turnover, indicate that momentum and liquidity are independent as irrespective of the liquidity stratum or weighting mechanism, momentum remains significant with past winners consistently outperforming past losers. However, the results in terms of interaction are semi-consistent, but for different reasons. The independent sorts on turnover and momentum depict that momentum and liquidity maintain a negative relationship where the lower liquidity momentum premium exceeds that of its higher liquidity counterpart. The main source of the return is attributable to the extreme poor performance of the low liquidity loser portfolio. Similarly, the dependent sort dynamic weighting test portfolios that simulated the conventional liquidity premium (up-weighting low turnover winner shares and down-weighting high turnover losers) produces average excess returns that are greater than the inverse liquidity weighted, equally weighted and market capitalization weighted momentum premiums.

Once again the long-only momentum returns are not significantly different under the differing liquidity weighting schematics, yet high liquidity losers produce returns lower than their low liquidity counterparts. The results of the dependent and independent sorts therefore both indicate that momentum and liquidity maintain a negative interaction, but are not consistent in terms of the source of the negative relationship. Lastly, despite the identification of a distinct inverse relationship, evidence of a liquidity premium on the cross-section of shares on the JSE is at best weak when considering the results of the independent sorts. The results therefore contradict the results of Page, Britten and Auret (2013) who found that momentum and liquidity (proxied by volume) maintain a positive relationship on the cross-section of shares listed on the JSE. By implication, the results therefore show that the interaction between liquidity and momentum may be risk based and inconsistent with herding.

4.3. BIVARIATE MOMENTUM SORTS ON REGRESSION BASED STYLES

The previous section focused on bivariate sorts that incorporated proxies based on stylistic anomalies that received attention in early works related to style based investment and refutations of the capital asset pricing model and market efficiency. Size, value and turnover

are similar in that all are relatively easy to calculate and extract from current share price and accounting information. The study now shifts focus to stylistic factors that have received growing recent interest and can be separated from size, value and momentum as they are more data and computationally intensive, requiring ordinary least square regression (OLS hereafter) in order to determine cross-sectional factor proxies or styles. Although the basic portfolio sorting methodology is identical, a further set of requirements are applied in order to ensure that regressed proxies are accurate and statistically reasonable. The augmented methodology applied to the secondary set of styles (regressed styles) is described in the section that follows.

4.3.1. Application of regressed proxies for the purposes of conducting stylistic sorts

The R squared dictates the percentage of variation in the dependent variable explained by the independent variable(s) while the standard error determines the relative accuracy and distributional properties of the produced coefficient. By design, the higher the R squared, the more reliance one can place on the regression output and similarly, the lower the standard error of the regression output, the closer the coefficient/parameter is to the true population parameter. The result of the regression analysis is therefore twofold. Firstly, the application of regression based proxies' shortens the sample period by sixty months. Secondly, the effective investable universe at each portfolio sort is narrowed as shares now require at least 36 months of historical return data. The ultimate result is that the sample and tests produced are now more exposed to survivorship bias, however the fact that the dataset explicitly holds delisted shares and utilises two portfolio start dates should mitigate any significant survivorship bias effects.

4.3.1.1. Momentum and idiosyncratic risk

The low volatility anomaly is one of the more recent stylistic factor mispricing's that has garnered significant popularity over a relatively short period of time. A number of studies have alluded to the possible inverse relationship between returns and idiosyncratic risk as early as Black (1972) and Haugen and Heins (1975) where both studies found that the relationship between risk and return was flatter than that predicted by the CAPM. Haugen and Heins (1975) stated that the empirical relationship between the conventional measures of risk and return is in fact inverted. More recently, Ang, Hodrick, Ying and Zhang (2006, 2009) showed that low volatility shares have significantly outperformed high volatility shares both in the US and across international markets.

Blitz and van Vliet (2007) found that the volatility anomaly is robust across equity markets and consistent even when controlling for size, value and momentum. Baker, Bradley and Wurgler (2011) found that low volatility shares outperformed high volatility shares on the US exchanges (via the CRSP) over the period January 1968 to December 2008, on both a nominal and real basis. Evidence of the low volatility anomaly presents a significant challenge to the efficient market hypothesis and rational risk-based asset pricing as the additional return generated from a low volatility strategy would imply an investor bearing a higher level of 'risk'. The lack of a coherent risk based explanation behind the low volatility conundrum has resulted in a number of behavioural explanations, namely representativeness and self-attribution biases per Kahneman and Tversky (1974, 1979) as well as the limits to arbitrage hypothesis described by Pontiff (1996).

Baker *et al.* (2011) found that behavioural theories best explain the low volatility anomaly as market participants are irrational and maintain a preference for volatile stocks due to representativeness and self-attribution bias.

Representativeness manifests in investors incorrectly evaluating the full set of information available and focusing on high risk shares that are irrationally expected to provide high value pay-offs in the near term. Self-attribution bias or overconfidence translates into the demand for high volatility shares as overconfidence is seen to be greater in shares that have greater levels of uncertain outcomes and are hence more volatile. Conversely, the limits to arbitrage argument has been addressed as another plausible cause of the low volatility effect. Pontiff (1996) hypothesized that smart money or arbitrageurs are limited from engaging in trading activity that would result in the trading away of pricing anomalies. Pontiff (1996) and Shleifer and Vishny (1997) found that idiosyncratic risk is the primary holding cost of engaging in arbitrage, possibly resulting in arbitrageurs limiting their capital exposure to stylistic strategies and therefore failing to trade away mispricing, resulting in the persistence of an anomaly through time. Relating this to the low volatility anomaly, a requirement to fully engage in such a strategy would be the shorting of a high volatility portfolio, implying that arbitrageurs would need to absorb a significantly high level of arbitrage holding costs. The implicit result is a lack of arbitrage capital being utilised to engage in low volatility strategies, resulting in a persistent anomaly that can expectantly grow as markets and equities become more volatile.

McLean (2010) conducted a study on the limits to arbitrage and the effects of idiosyncratic risk on momentum and long-term reversal strategies. The author found that momentum failed to maintain any distinct relationship with idiosyncratic risk, implying that limits to arbitrage could not explain the momentum anomaly on the cross-section of shares listed in the US over the period January 1965 to December 2004. Page, Britten and Auret (2016) consider idiosyncratic

risk and its interaction with size, value and momentum on the cross-section of shares listed on the JSE. Instead of dual sorts, T-GARCH and GARCH-in-the-mean models were used to determine the relationship between idiosyncratic risk and the styles considered. Like McLean (2010), it was found that idiosyncratic risk maintained a weak inverse relationship with momentum. Conversely, value seemed to maintain a positive relationship with idiosyncratic risk, leading to the conclusion that the limits to arbitrage hypothesis explains value but not momentum.

The purpose of the following tests to be conducted are therefore two-fold. Firstly, bivariate independent and dependent sorts will allow for the determination of independence and interaction between momentum and idiosyncratic risk, assuming that idiosyncratic risk is merely a stylistic anomaly. However, a natural corollary to the interaction hypothesis is a 'limits to arbitrage' test. If momentum maintains a positive relationship with idiosyncratic risk, the limits to arbitrage explanation contains merit in explaining the existence and persistence of momentum on the cross-section of shares listed on the JSE. If, however, momentum maintains a neutral or negative relationship with idiosyncratic risk, then the findings will be consistent with the evidence presented by McLean (2010) and Page, Britten and Auret (2016), indicating that the momentum premium cannot be explained by limits to arbitrage. Lastly, Rachev, Jasic Stoyanov and Fabozzi (2007) found that momentum strategies that used risk-reward criterion, as opposed to cumulative historical returns, achieved economically lower momentum profits when compared to the conventional sorting methodology but were superior on a risk-adjusted basis. The results will therefore provide clarity regarding the combination of momentum and idiosyncratic risk as an optimal style combination on a gross and risk-reward criterion basis.

4.3.1.2. Bivariate independent sorts on momentum and idiosyncratic risk

The portfolio sorting methodology applied in defining the momentum - idiosyncratic risk portfolios is virtually identical to that applied in the bivariate independent sorts conducted on size, value and turnover. At each portfolio selection date, shares are classified based on their six minus one month cumulative historical momentum and t idiosyncratic risk measured over the previous 36 to 60 months. The methodology applied in defining idiosyncratic risk resembles that described by McLean (2010) as idiosyncratic risk is measured post orthogonalization on the JSE All-share index portfolio (J203 hereafter). The purpose of the orthogonlised idiosyncratic risk measure, as opposed to a univariate measure calculated using only the historical return series, is that orthogonalization allows for the determination of idiosyncratic risk that excludes market risk. The danger of not extracting market risk in the

estimation of idiosyncratic risk is that profits attributable to the idiosyncratic sort could potentially be driven by the low beta anomaly, which is to be discussed in the following section. The method can therefore be seen as purer method of defining firm specific risk exclusive of market risk. Methodologically, the idiosyncratic risk for each share is measured by first orthogonalizing the gross share return series on the market proxy via OLS regression and using the residual series in order to determine idiosyncratic risk. Mathematically, the idiosyncratic risk measure follows

$$y_{i,t} = \alpha_i + \beta_i J203_t + \varepsilon_{i,t} \quad (4.9)$$

$$\overline{y_i} = \alpha_i + \beta_i J203_t \quad (4.10)$$

$$y_{i,t} - \overline{y_i} = \varepsilon_{i,t} \quad (4.11)$$

$$\sigma_i = \sqrt{\sum_{t=1}^{n} \frac{\varepsilon_{i,t}^2}{n-2}} \quad (4.12)$$

Where y_{it} is the return on share i at time t, y_i hat is the expected return of share i based on market model estimated per equation 4.9, J203 is the return on the JSE all-share at time t and e_i is the error/residual term of the time-series OLS regression. The squared error/residual term is then cumulated (generally referred to as the sum of squared errors) and scaled by the number of historical months (n) less two to account for the estimated regression parameters (n-2 degrees of freedom). Portfolio sorts are conducted on a semi-annual basis over the period January 1996 to June 2015. Once again, shares are initially filtered on transaction costs and liquidity, proxied by price, cumulative zero daily trades over the previous year and average turnover. For the purpose of inclusion, shares require a price in excess of 100 cents, cumulative zero daily trades over the previous year less than 100 and have a turnover ratio above the cross-sectionally measured 10th percentile. As mentioned, an additional set of filters are applied as shares require a minimum of 36 months of historical returns at each sorting period and a time-series regression R squared that is in excess of the cross-sectionally measure 10th percentile.

At each portfolio sorting date, shares are independently sorted into one of three portfolios based on momentum and idiosyncratic risk using a 33rd / 66th percentile split. The result is nine portfolios sorted on momentum and idiosyncratic risk where constituent shares are assigned an equal weight at portfolio formation. Portfolio returns are then calculated for the following six months assuming buy-and-hold. If a share delists during the portfolio period, the share is

assigned a -100% return. Consistent with the portfolio sorts described above, two portfolio start dates are applied, namely January and June 1997. The final portfolio return is an equally weighted time-series of the two start date portfolios, resulting in a final portfolio return that is free of beginning and end of sample bias. The results of the independent sorts on idiosyncratic risk and momentum are described in the table that follows.

	Winner	Medium	Loser	WML
High Volatility	1.2871%	0.3814%	-0.4617%	1.7488%
	0.0014***	***0.3357***	***0.2692***	***0.0000******
Medium Volatility	1.4892%	0.9346%	0.3366%	1.1526%
	0.0001***	***0.0073******	***0.3644***	***0.0005******
Low Volatility	1.0947%	1.1032%	1.0006%	0.1123%
	0.0024***	***0.0004******	***0.0037******	***0.7159***
LVMHV	-0.1924%	0.7218%	1.4623%	
	0.5747	***0.0316****	***0.0000******	

*Table 4.11: Portfolios sorted on six minus one month cumulative momentum and idiosyncratic risk. P-values are assigned asterisks based on statistical significance where *,**,*** indicate significance at the 10%, 5% and 1% level. All returns and performance statistics are based on monthly returns and risk measures.*

The results of the independent sort on idiosyncratic risk and momentum indicate that contrary to the findings of McLean (2010) and Page, Britten and Auret (2016), as the momentum premium seems to have a positive relationship with idiosyncratic risk. The final column of the table depicts the zero-cost momentum portfolio assuming variation in the idiosyncratic risk stratum. The results indicate that as volatility decreases, the momentum premium decreases monotonically and experiences the most significant decrease in the low idiosyncratic risk-momentum test portfolios. The high idiosyncratic risk excess momentum return achieves an average monthly return of 1.75% per month and is significant at the 1% level. Conversely, the low idiosyncratic risk momentum excess return achieves an insignificant average monthly return of only 0.112%, equating to only 1.35% per annum.

Considering the source of the momentum excess average returns, the long only winner portfolios do not seem to display any consistent relationship with idiosyncratic risk, where the best performing portfolio is the medium idiosyncratic risk winner portfolio, achieving 1.49% per month and is significantly different from zero at the 1% level. The high volatility winner portfolios gross return is only 0.19% per month greater than that of the low volatility winner, with the difference not being significantly different from zero. Interestingly, when allowing for a variation in momentum beyond the winner portfolio, the low volatility anomaly seems to emerge. Both the medium and low momentum portfolios depict a significant low volatility

premium as the long only portfolio returns increase monotonically given a decrease in idiosyncratic risk. The medium momentum portfolio high idiosyncratic risk portfolio achieves an average return of 0.381% while its low idiosyncratic counterpart achieves a gross monthly average return of 1.1% per month and is significant at the 1% level. The zero cost (low minus high) volatility premium is 0.72% per month and is significantly different from zero at the 5% level of significance.

The low volatility premium increases to its pinnacle in the low momentum portfolios, achieving a low volatility premium of 1.462% per month that is significant at the 1% level. The major contributor to the non-existent momentum premium achieved in the low volatility sort is largely attributable to the extremely positive performance of the low volatility loser portfolio. The results indicate that within independent sorts, momentum is to some extent not independent of volatility and furthermore, the interaction between momentum and volatility is in fact inverse. One can reject the independence hypothesis based on the momentum premium only being significant and present in the high and medium volatility momentum terciles. Similarly, the fact that the momentum premium decreases to the point of insignificance when moving across the idiosyncratic risk stratum results in a further rejection of the null interaction hypothesis.

Relating this to the findings of McLean (2010), the results of the long only portfolios are largely consistent with momentum not being affected by variations in idiosyncratic risk. This is best displayed by the insubstantial difference in the excess return between low and high volatility winner shares. However, when extending the analysis to include the loser portfolio, the zero cost momentum strategies depict a significantly positive relationship between momentum and idiosyncratic risk. Such evidence is an extreme rejection of the evidence expounded by McLean (2010) and Page, Britten and Auret (2016). The limits to arbitrage hypothesis dictates that stylistic anomalies persist due to smart money not being able to trade away mispricing as the costs of conducting the arbitrage strategy offset the marginal benefit or profit realised. Pontiff (1996) argued that idiosyncratic risk is the single greatest limit to arbitrage, defining idiosyncratic risk as the ‘holding cost’ of the arbitrage strategy. A clear relationship can therefore be defined where the higher the idiosyncratic risk, the higher the holding costs of trading on the mispricing and therefore the greater the chance of the mispricing persisting through time. The findings per Table 4.11 indicate that the persistence and significance of the momentum premium found on the cross-section of shares listed on the JSE may be attributable to momentum being positively related to volatility and therefore driven by the inability of smart money to correct the mispricing.

A further explanation of the positive relationship between idiosyncratic risk and momentum can be linked to the findings of Conrad and Kaul (1998). The authors hypothesized that the

momentum anomaly is not produced through time-series return continuation but rather through the purchase of high mean return shares and simultaneous selling of low mean return shares. The authors presented evidence in favour of their hypothesis through conducting an empirical test where share returns where randomised in terms of the time-period in which they occurred. The authors then sorted portfolios using the scrambled returns and found a significant momentum premium. Secondly, the authors conducted simulations where the fictitious returns were mean stationary. The authors found that a key requirement for the momentum premium is cross-sectional diffusion in mean returns, implying that the momentum premium is positively related to cross-sectional diffusion or market volatility. The findings presented in table 4.11 are consistent with the hypothesis of Conrad and Kaul (1998) as momentum seems to maintain a positive relationship with volatility, to the extent that the most extreme volatility tercile produces the largest momentum premium.

The results presented thus far in both this chapter and Chapter Three indicate that momentum is persistent across styles and therefore independent, yet the findings above could be interpreted as consistent with the limits to arbitrage hypothesis as well as the findings of Conrad and Kaul (1998). Since the momentum premium is shown to display a positive relationship with idiosyncratic risk, one can assume that the momentum premium persists due to the high costs of arbitrage associated with momentum, specifically the shorting of loser shares. Similarly, the positive relationship between momentum and idiosyncratic may be driven by high levels of cross-sectional diffusion being a prerequisite for the momentum premium. Notably, the results presented in Table 4.11 indicate that there is a significant low volatility premium on the JSE, a phenomenon that has been largely unexplored in local literature. Further, the low volatility premium is most prominent in the lower momentum stratum, where a large proportion of the excess return is derived through the short position in the high volatility loser portfolio. Uniquely, the high volatility loser portfolio achieves the worst return of -0.462% per month, or -5.54% per annum.

4.3.1.3. Bivariate dependent sorts on momentum and idiosyncratic risk

The results of the independent sorts on momentum and idiosyncratic risk present evidence that is largely inconsistent with local and international findings, as momentum seems to maintain a positive relationship with idiosyncratic risk and is therefore consistent with the limits to arbitrage hypothesis. As discussed previously, the sole purpose of the bivariate dependent sorts is to further augment the test and possibly negate the potential biases that could arise from the relatively limited universe of investable shares. The current set of bivariate tests utilise regressed factors and therefore apply a further set of restrictions when sorting shares

compared to the likes of value, size and liquidity. In order to understand the effects of the additional filters, the number of shares per portfolio sort are analysed in order to determine the effects of the additional filters on the investable universe of shares.

Reporting only on the high and low idiosyncratic risk winner portfolios, the average number of shares at each sort for the high volatility-high momentum portfolio is 32, with a maximum of 56 shares and a minimum of 9 shares over the sample period. However, the effect on the low idiosyncratic risk-high momentum test portfolio is more drastic where the average number of shares is 19, the maximum is 34 and the minimum number of shares is 5 over the sample period. The difference in the average number of shares of 12 is significant at the 1% level. The implication is therefore that the independent sort results could be biased by the number of shares per test portfolio, resulting in higher levels of noise and industry bias due to lack of diversification. Additionally, McLean (2010) utilised a bivariate dependent strategy that utilised weighting based on idiosyncratic risk as a means of determining the relationship between momentum and volatility. Therefore, the dependent sort results to be conducted will be more methodologically consistent for the purposes of comparison.

The bivariate dependent sorts are conducted in order to mitigate the effects of a limited investable universe by sorting initially on momentum and then using a weighting schematic to weight towards the 'other' considered style's expected premium. In the case of momentum and idiosyncratic risk, the expected volatility premium is found in low idiosyncratic risk shares. Portfolios are initially sorted into quintiles based on each shares six minus one cumulative historical return. Shares are once again filtered along price and liquidity criteria, proxied by zero daily trades and historical turnover over the previous twelve months. Constituent shares are then assigned initial weightings based on their idiosyncratic risk orthogonal to the J203, estimated using an historical window period of between 36 to 60 months. In order to mimic the low volatility effect, within the higher momentum test portfolios, constituent shares assigned initial weightings based on the inverse of idiosyncratic risk, while the inverse is applied to the lower momentum test portfolios. More formally, the dynamic weighting mechanism can be described mathematically via

$$W_i = \left(\frac{1}{\sigma_i} \middle| P = 1,2,3\right) \qquad (4.13)$$

$$W_i = (\sigma_i | P = 3,4,5) \qquad (4.14)$$

Where W_i is the initial weighting assigned to each share at portfolio initiation, σ_i is the idiosyncratic risk of share i which is orthogonal to the J203 All share index and P represents the quintile test portfolio where P1 implies the highest "winner" momentum portfolio and P5

the lowest “loser” momentum portfolio. As mentioned, portfolios are sorted on a semi-annual basis where two portfolio initiation dates are assumed, namely January and June 1997. Portfolio returns are then calculated on a buy-and-hold basis where constituent share weightings are allowed to vary post sort until the next portfolio sorting period. The results of the dependent bivariate sorts are depicted in the table that follows.

	P1	P2	P3	P4	P5	P1-P5
Mean Return	1.5607%	1.1079%	0.7530%	0.4750%	-0.1321%	1.6928%
P-value	***0.0001******	***0.0001******	***0.0306****	***0.1894***	***0.7286***	***0.0000******
Sharpe	0.270	0.234	0.145	0.088	-0.023	0.325
Treynor	0.020	0.017	0.011	0.007	-0.002	0.227

*Table 4.12: Bivariate dependent sorts on momentum and idiosyncratic risk. P-values are assigned asterisks based on statistical significance where *,**,*** indicate significance at the 10%, 5% and 1% level. All returns and performance statistics are based on monthly returns and risk measures.*

The results presented in Table 4.12 largely contradict those seen in the independent sorts. As momentum test portfolios vary from portfolio one (winners) to portfolio five (losers), average gross monthly returns and risk-return criteria decrease monotonically. The extreme winner portfolio (P1) achieves an average monthly return of 1.56% and is significant at the 1% level. The extreme loser portfolio (P5) achieves an insignificant average monthly gross return of -0.13%, equating to -1.56% per annum.

The final column depicts the momentum excess return premium represented as the zero cost arbitrage portfolio achieved by fictitiously investing in the winner portfolio and simultaneously shorting loser portfolio. The excess return premium is 1.69% per month and is significant at the 1% level, equating to 20.28% per annum over the sample period. On a risk-adjusted basis, the excess momentum test portfolio achieves the highest Sharpe and Treynor ratios, producing 32 basis points per 1% of idiosyncratic risk and 23 basis points per unit of market risk. The results therefore show that the momentum premium is present when applying the dynamic weighting mechanism that over weights low volatility shares in the higher momentum test portfolios and conversely over weights high volatility shares in the lower momentum test portfolio stratum. Since the results depict a clear and significant momentum premium, the independence hypothesis is rejected, however further analysis is required to determine the interaction between momentum and volatility.

In order to define the relative performance of the dynamically weighted low volatility momentum sort, the excess return premium is compared to those achieved by the equally and value weighted momentum quintile sorts, conducted over the same sample period with identical price and liquidity filters applied. The equal and value weighted quintile sorts are

presented in the tables that follow and differ to those presented in tables 4.2(i) and 4.2(ii) due to the shortened time frame considered.

	P1	P2	P3	P4	P5	P1-P5
Mean Return	1.5810%	0.9913%	0.7715%	0.5334%	0.0805%	1.5005%
P-value	***0.0001******	***0.0023******	***0.0205****	***0.1156***	***0.8238***	***0.0000******
Sharpe	0.265	0.207	0.157	0.106	0.015	0.314
Treynor	0.019	0.015	0.011	0.008	0.001	0.117

*Table 4.12(i): Equivalent Equally Weighted Quintile Portfolio Sorts over the regressed variable dependent sort time period. P-values are assigned asterisks based on statistical significance where *,**,*** indicate significance at the 10%, 5% and 1% level. All returns and performance statistics are based on monthly returns and risk measures.*

	P1	P2	P3	P4	P5	P1-P5
Mean Return	1.6642%	1.0548%	0.8181%	0.5847%	0.1182%	1.5460%
P-value	***0.0000******	***0.0013******	***0.0148****	***0.0905****	***0.7498***	***0.0000******
Sharpe	0.273	0.218	0.165	0.114	0.021	0.311
Treynor	0.019	0.015	0.011	0.009	0.002	0.116

*Table 4.12(ii): Equivalent Value Weighted Quintile Portfolio Sorts over the regressed variable dependent sort time period. P-values are assigned asterisks based on statistical significance where *,**,*** indicate significance at the 10%, 5% and 1% level. All returns and performance statistics are based on monthly returns and risk measures.*

The comparison of results will allow for the determination of whether the dynamic weighting methodology produces a momentum premium that is in excess or below the generic (equal and market capitalization) weighting methodologies. A lower premium would indicate that the dynamic weighting methodology maintains a negative interaction with momentum, while a higher premium would imply the inverse conclusion, specifically that momentum maintains a positive relationship with the stylistic weighting methodology. The comparative results are depicted in Table 4.13 below.

	Low Volatility Premium Weighted	Equally weighted	Value Weighted
Mean Return	1.6928%	1.5005%	1.5460%
P-value	***0.0000******	***0.0000******	***0.0000******
Sharpe	0.325	0.314	0.311
Treynor	0.227	0.117	0.116

*Table 4.13: Dynamic style weighted momentum versus equal and value weighted momentum premia. P-values are assigned asterisks based on statistical significance where *,**,*** indicate significance at the 10%, 5% and 1% level. All returns and performance statistics are based on monthly returns and risk measures.*

The results presented in Table 4.13 above cast doubt on the results of the independent sorts. Per tables 4.12(i) and 4.12(ii), over the regressed factor variables sample period (January 1997 to June 2015), the equal and value weighted momentum sorts achieve excess returns of 1.50% and 1.55% respectively, both being significant at the 1% level. As mentioned, the low-volatility weighted momentum premium achieves an average monthly return of 1.69% per month, implying an additional return premium over the equal and value weighted sorts of 19 and 15 basis points per month, equivalent to 2.31% and 1.76% per annum. Furthermore, the low volatility weighted momentum premium achieves a marginally higher Sharpe ratio, 32 basis points per one percent of standard deviation compared to 31 basis points achieved by the equally and value-weighted momentum sorts. On a market risk basis, the low volatility premium weighted momentum sort achieves a Treynor ratio nearly double that of the equal and value weighted premia.

The bivariate dependent sort results are therefore highly consistent with the evidence presented by McLean (2010) and Page, Britten and Auret (2016). McLean (2010) found that idiosyncratic risk maintained a positive relationship with long-term reversal and value, fitting neatly within the limits to arbitrage explanation. Conversely, the study found that the relationship between momentum and idiosyncratic risk was negligible, if not slightly negative. Similarly, Page, Britten and Auret (2016) found that momentum seemed to maintain a negligible relationship with idiosyncratic risk, where idiosyncratic risk was measured via GARCH-in-the-mean and asymmetric GARCH. The study found that unlike the value premium, the momentum premium fails to adjust to shifts in idiosyncratic, implying that limits to arbitrage is not a plausible explanation of the momentum premium on the cross-section of shares listed on the JSE.

The findings per Tables 4.12 and 4.13 indicate that momentum maintains a negative relationship with volatility, implying that the momentum premium cannot be explained by the limits to arbitrage hypothesis. Firstly, Table 4.12 clearly indicates that overweighting low volatility winners and high volatility losers does not reduce the momentum premium. Further, table 4.13 clearly indicates that a momentum portfolio that over weights low volatility winner shares and simultaneously over weights high volatility loser shares in lower quintile portfolios achieves excess returns greater than conventionally estimated equal and value weighted momentum portfolios. Furthermore, the combination of momentum and volatility produces significantly higher returns than generic weighting mechanism, implying an optimal investment strategy that exceeds equal and value weighted momentum sorts by 2.31% and 1.76% per annum. The obvious remaining question is why the extreme disparity between the independent and dependent sort results? At face value, the independent sorts are severely

disadvantaged by the low number of shares per the low volatility, high momentum portfolios. Unfortunately, one cannot currently draw an efficient conclusion as to which is the more accurate result as the tests produce polar opposite conclusions. The only means of efficiently determining the relationship between momentum and idiosyncratic risk is left to the multivariate regression analysis to be conducted in the chapter that follows. Using the momentum test portfolios as dependent variables, multivariate time-series regressions are to be conducted utilising the various style premiums explored in the current chapter. The final conclusion regarding the relationship between momentum and idiosyncratic risk will therefore be postponed until re-considered in the time-series attribution tests.

4.3.2. Momentum and beta

Market Beta ("beta" hereafter) as described by the capital asset pricing model ("CAPM") of Sharpe (1964), Lintner (1965) and Mossin (1965) is defined as the sole determinant of risk required to describe expected return. Unfortunately, beta and the CAPM have been the target of an academic onslaught of counter CAPM and market efficiency evidence that effectively disproves the notion of market risk being the central explanatory variable able to describe the cross-sectional variation in share returns. Probably the greatest refutation of the CAPM is the presence of the low beta anomaly, which has garnered recent attention across various markets. Black (1972) asserted that the relationship between expected return and risk is significantly flatter than that which is predicted by CAPM.

A number of studies have extended the contrary evidence by proving that the conventional measures of risk such as idiosyncratic and market risk maintain a negative relationship with expected returns, implying an inverse relationship to that which is prescribed by the portfolio theory, the efficient market hypothesis and CAPM. Van Rensburg and Robertson (2003) alluded to the low beta anomaly when evaluating size and value on the cross-section of shares listed on the JSE. The authors found that portfolios sorted on pre-ranking market beta displayed an inverse relationship with expected returns, where the lowest beta portfolio achieved returns in excess of the high pre-ranking beta quartile portfolio.

Baker, Bradley and Wurgler (2011) considered the period January 1968 to December 2008 and using the cross-section of shares per the CRSP database, found that a single dollar invested in the low beta portfolio achieved a final portfolio value of $60.48 in nominal terms ($10.28 on an inflation adjusted basis) while the high beta portfolio achieved a final nominal portfolio value of $3.77 or $0.64 in real terms. The net result was that over the sample period, the cumulative outperformance of low beta shares over their high beta counterparts amounted to 964%, implying an outperformance of 1.95% per month.

More recently, Frazzini and Pedersen (2014) found that the low beta anomaly was present across global markets and asset classes. The study considered listed equities covering 20 countries where the US test considered all shares per the CRSP database over the period January 1926 to March 2012 while international equities were sourced from the Xpressfeed database, representing equities that make up the MSCI developed universe over the period January 1989 to March 2012. The test also included sovereign country bonds, foreign exchange, US treasury bonds, credit indices, corporate bonds and commodities. Focusing on US equities, shares were sorted into one of ten decile portfolios based on their *ex ante* time-series betas measured using daily returns over the previous 12 to 36 months. Betas were adjusted using the Bayesian adjustment per Vasicek (1973) where betas were shrunk to tend closer to the cross-sectional average beta in order to mitigate the effects of outliers and thin trading. Using a series of attribution models, the authors found that alphas declined monotonically from low beta to high beta portfolios. In addition, the authors constructed a fictitious zero cost beta portfolio, referred to as the 'BAB' (betting against beta) portfolio. The BAB portfolio produced significant alphas of 0.73%, 0.55% and 0.55% per month using the Fama-French, Carhart and liquidity augmented Carhart models respectively. Importantly, the results extended to each asset class considered, implying that the low-beta phenomenon is globally priced and extends beyond the universe of equities.

The presence of the low beta anomaly defies explanation on a risk basis as the argument is naturally illogical, where additional return is a result of higher risk exposure in low market risk shares. Naturally, the implausibility of a risk explanation led to a number of studies considering behavioural explanations of the low beta anomaly. Baker, Bradley and Wurgler (2011) asserted that both the low volatility and low beta anomaly are consistent with irrational investor behaviour and limits to arbitrage. The authors rely on two behavioural biases based on the work of Kahneman and Tversky, namely representativeness and overconfidence. Representativeness implies that investors do not rationally explore the current set of facts but rather base decisions on non-representative data. In application to high market risk shares, investors generally constrain the investable universe to large market capitalization, popular shares that typically maintain a high correlation with the market. The second behavioural bias, overconfidence, implies that investors overestimate the precision of their own forecasts.

Baker *et al.* (2011) relate overconfidence to divergence in opinions relating to shares, where greater divergence entails higher idiosyncratic and market risk as high growth or extreme loser shares generally garner the more attention. Central to linking overconfidence to the demand for high market risk shares is the limited ability to short high beta shares, where optimists dominate the price setting and purchase of the high beta shares while pessimists are limited

in their ability to conduct any form of arbitrage. Lastly, the limits to arbitrage explanation is considered from a perspective of benchmarking. The authors note that fixed mandate large scale institutional investors are largely confined to benchmarks that are market weighted and inherently low beta. Such an example would be most SA fund managers being constrained to invest in the ALSI top 40. The result is that the limits to arbitrage of benchmarking prevent smart money from benefitting from the low beta anomaly and conversely, encourage investment in high beta shares.

Akin to the overconfidence explanation offered by Baker, Bradley and Wurgler (2011), Hong and Sraer (2013) developed a behavioural model that explains the low beta anomaly where high beta shares are more prone to speculative overpricing. The central premise of the model relies on investors disagreeing about the future cash flows of the company (divergence of views) and the limited ability to short sell. The logic of the model implies that optimists and pessimists maintain views regarding factors related to the market and the future cash flows of each share. A short-selling limit naturally hampers the actions of pessimists, hence prices are set by optimists[10]. The authors assert that popular high growth shares generally have a greater divergence of opinion related to future cash flows and therefore are naturally higher beta and are overbought. In simulation tests, the authors found that high beta shares are overpriced when there is a high level of disagreement relating to either the market or the shares future cash flows. Furthermore, there is little price correction as market participants with pessimistic market views are limited to exercise their belief due to short-sale constraints.

The central result of the theoretical model is that in times of extreme divergent views, optimists are price-setters, resulting in the high beta shares being overpriced in relationship to low beta shares. However, in time periods where there is a non-divergence of views, the low volatility and low beta anomaly produces negative returns. In empirical tests, the standard deviation in analysts' forecasts of growth is used as the proxy for divergence of opinion. The proxy is applied in regression analysis where the dependent variable is the excess return on beta sorted test portfolios. Consistent with propositions of the theoretical model, the excess returns of the high beta portfolios are increasing given a decrease in the level of divergent views while the opposite occurs when the level of divergent views are high. The implication of the results is that the low beta phenomenon is largely based on the level of divergent views, resulting in low beta shares achieving significant excess returns over their high beta counterparts in times of extreme opinions regarding the future assumptions about the market and company earnings.

[10] Consistent with the findings of Miller (1977)

Frazzini and Pedersen (2014) relate the low beta anomaly to leverage and margin constraints that vary through time and across individuals. The premise of the model differs marginally to the explanations presented above, as the requirement is not the divergence of views but rather that most investors are constrained to purchase high beta assets as in order to introduce artificial leverage. The reason behind high beta shares being overpriced is that investors, such as mutual funds, are constrained to invest in higher beta shares as high beta shares, which are more risky by definition, provide higher levels of artificial leverage when compared to low beta shares. Since most investors are constrained by the level of leverage they can use to up-weight and effectively up-risk their investment strategies, the only viable option is to weight towards higher beta shares. The implication of the proposed model is that the low beta phenomenon is driven by leverage and margin constraints as investors' prefer embedded leverage as opposed to purchasing low beta shares using a leveraged position.

As mentioned above, the authors find evidence of the low beta anomaly across various international equity markets and asset classes, but in order to test the driver of the phenomenon, the authors use the lagged and contemporaneous TED spread, the difference between rates on interbank loans and US treasury bills, as a proxy for funding liquidity risk and margin constraints. The authors find that the BAB factor, estimated across asset classes, is negatively related to both the current and lagged TED spread, implying that the low beta phenomenon is largely driven by the general funding (leverage) constraints prevailing in the market. Additionally, the authors included additional tests that separate idiosyncratic risk and market risk. Both Baker, Bradley and Wurgler (2011) and Hong and Sraer (2012) developed integrated models that happen to explain both the low volatility and low beta phenomenon. Frazinni and Pedersen (2014) sorted low beta portfolios and simultaneously controlled for idiosyncratic risk. The authors found that idiosyncratic risk weighting had little effect on alphas generated by the beta sorted portfolios, implying that the low beta anomaly is independent of the low volatility anomaly. The results of the study therefore provided a consistent explanation of the low beta anomaly that is driven by leverage constraints and independent to the low volatility anomaly.

The tests that follow intend to determine the independence and interaction between momentum and the low beta effect. A corollary to the test is the determination of whether the low beta phenomenon is present in the cross-section of shares listed on the JSE. Importantly, the tests that follow do not consider the theoretical drivers of the low beta anomaly as such would be beyond the scope of this study.

4.3.2.1. Bivariate independent sorts on momentum and beta

The bivariate independent sorts to be conducted are virtually identical to those described above where shares are sorted simultaneously on their six minus one month cumulative returns and market beta. Consistent with all sorts described thus far, at each portfolio sort date shares are evaluated along price and liquidity filters, where liquidity is proxied by the number of historical zero daily trades and average turnover ratio measured over the previous year. In order to ensure a highly liquid, tradable representation of both the momentum and beta sorts, the minimum price is set at 100 cents, the maximum allowable number of zero daily trades is 100 and shares that achieve a turnover ratio below the cross-sectionally measured 10th percentile are excluded. Further, in order to ensure optimal beta measurements, the required estimation window as described by Bradfield and Barr (1988, 1989) of between 36 to 60 months is applied, therefore an additional filter is applied where shares require at least 36 months of historical returns. The estimation of market beta has been highly topical with a number of studies considering the effects of liquidity, non-synchronous trading and return outliers on beta estimates.

Recently, McClelland, Auret and Wright (2014) considered a number of beta estimation techniques that correct for infrequent trading and market frictions in a simulated environment. The authors found that the superior beta correcting technique, when weighed against the complexity of performing the said technique, is an adjusted ordinary least squares beta that considers the cross-sectional variation in relative liquidity over the previous annum. The power of the technique can directly compared to those used by Frazzini and Pedersen (2014) who followed Vasicek (1973) and Elton, Gruber and Goetzmann (2003) in adjusting betas in order to mitigate the effects of outliers. The methodology employed by Frazzini and Pedersen (2014) simply weights all beta using a Bayesian adjustment[11] where each beta estimate is weighted towards the prevailing cross-sectional average. The adjustment can be expressed mathematically as

$$\beta_{i,Adj} = w\beta_{i,TS} + (1 - w)\beta_{i,CSA} \qquad (4.15)$$

Where $\beta_{i,Adj}$ is the adjusted beta of share i, w is the weighting set at 0.6, $\beta_{i,TS}$ is the time-series estimated beta via OLS and $\beta_{i,CSA}$ is the cross-sectional average of all shares at the time of estimation. McClelland, Auret and Wright (2014) proved under simulation analysis that such techniques fail to weight betas correctly towards their true beta as the same blanket rule is applied to each share, irrespective of its unique trading and liquidity characteristics. The

[11] Per Vasicek (1973) and more recently Elton, Gruber and Goetzmann (2003)

method espoused by McClelland, Auret and Wright (2014) corrects for market frictions by adjusting time-series betas using the specific shares trading dynamics over a pre-specified period. The power of the adjustment therefore corrects time-series betas using a correcting factor that varies cross-sectionally and through time for each share. The beta adjustment per McClelland, Auret and Wright (2014) can be described mathematically as

$$\beta_{i,Adj} = \beta_{i,TS}\delta_i \qquad (4.16)$$

$$\delta_i = \frac{TD}{(TD - \sum ZDT_i)} \qquad (4.17)$$

Where the time series beta ($\beta_{i,TS}$) is estimated via OLS regression using the J203 as the independent variable and adjusted for market frictions using a ratio (δ) equal to the number of trading days over the previous year (TD), scaled by the trading days over the previous year less the cumulative number of zero daily trades over the previous trading year for share i (ZDT_i). Importantly, shares that achieve a negative betas are excluded while the maximum number of zero daily trades applied across all of the independent sorts is equal to 100. The implication of the adjustment under the current liquidity filter results in the maximum and minimum value of the adjustment factor δ being approximately equal to 1.67 and 1 respectively, assuming total number of trading days per year equal to 250. The results of the bivariate independent sorts on momentum and market beta are presented in the table that follows.

	Winner	Medium	Loser	WML
High Beta	1.3781%	0.8264%	-0.4094%	1.7876%
	0.0003* **	**0.0388** **	**0.3275**	**0.0000*** **
Medium Beta	1.2189%	0.9042%	0.4813%	0.7376%
	0.0019* **	**0.0087*** **	**0.1793**	**0.0119** **
Low Beta	1.4141%	0.8495%	0.7165%	0.6976%
	0.0000* **	**0.0056*** **	**0.0514***	**0.0318** **
LBMHB	0.0359%	0.0230%	1.1259%	
	0.9024	**0.9461**	**0.0021*** **	

*Table 4.14: Portfolios sorted on six minus one month cumulative momentum and market beta. P-values are assigned asterisks based on statistical significance where *,**,*** indicate significance at the 10%, 5% and 1% level. All returns and performance statistics are based on monthly returns and risk measures*

The results presented in the table above depict the gross average monthly returns of portfolios sorted independently on six minus one month cumulative return and liquidity adjusted beta per McClelland, Auret and Wright (2014). The far right column depicts the zero cost hypothetical long-short momentum excess returns while the bottom rows depicts the excess

returns of the fictional zero cost low minus high beta portfolio. Considering the momentum excess returns per the final column, all are positive and statistically significant, ranging from 0.7% to 1.78% per month, equating to 8.4% and 21.45% per annum. The results of the independent sorts therefore clearly indicate that the momentum premium is independent of beta as momentum is consistently positive and significant at the 5% (Medium and Low Beta) and 1% levels (High Beta), irrespective of the market beta stratum. The same conclusion cannot be applied to the interaction between momentum and market beta, as the momentum premium decreases monotonically with beta, implying a positive relationship.

The high beta momentum premium achieves an average monthly return of 1.79% per month while the low beta momentum average monthly premium is 0.7% per month, implying that the high beta momentum premium is effectively 2.56 times greater than its low beta counterpart. Additionally, the average difference between the high and low beta momentum premium 1.09% per month, equating to 13.08% per annum and is significant at the 5% level. In order to evaluate the source of the variation in the momentum premiums, the long only gross portfolio returns are analysed. Considering the winner portfolios across the market beta sorts, the high beta winner portfolio achieves a monthly average return of 1.38% while the low beta winner portfolio achieves 1.41% per month, both of which are significant at the 1% level.

The relative outperformance of the low beta winner portfolio over its high beta counterpart is minimal and insignificant, equating to 0.036% per month on average. The major source of the momentum premium seems to be largely driven by the variation in returns across the beta stratum in the loser portfolios. The high beta loser portfolio achieves an insignificant negative monthly average return of -0.41% per month, equating to -4.9% per annum. Conversely, the low beta loser portfolio achieves a monthly average return of 0.72%, equating to 8.6% per annum and is significant at the 10% level. The average monthly difference between the low and high beta loser portfolio is 1.13% per month and is significant at the 1% level. The results therefore imply that the negative relationship between momentum and beta is largely driven by the short position in the loser portfolio, where the low beta loser portfolio significantly outperforms its high beta counterpart.

Additionally, the results produce interesting findings related to the low beta phenomenon as the low beta similarly has negative relationship with momentum. The low beta premium (final rows of table 4.14, LBMHB) increases when moving from winner to loser shares, to the extent that the low beta premium is only significant in the loser share stratum, achieving 1.126% compared to 0.036% earned in the winner stratum. The implication of the finding therefore provides weak evidence of the beta phenomenon as unlike momentum, the low beta anomaly is only present in the lowest momentum stratum, implying that low beta is not independent of

momentum. Relating the results to evidence presented in literature, both van Rensburg and Robertson (2003) and more recently, Gilbert, Strugnell and Kruger (2011) found indirect evidence of the low beta anomaly. Van Rensburg and Roberston (2003) found that monthly sorted portfolios formed on pre-ranking beta produced returns that displayed an inverse relationship with market risk as portfolio returns increased monotonically when moving from the high beta to low beta quintile. Moreover, the low beta portfolio earned 0.9% per month in excess of the high beta portfolio and was significant at the 5% level.

Gilbert, Strugnell and Kruger (2011) considered the results of van Rensburg and Robertson (2003) and furthered the study to include a longer and wider panel of shares and multiple beta estimation methods in order to account for thin-trading, namely the Scholes and Williams (1977) and Dimson (1979) beta adjustments. The authors found that when using conventional time-series OLS beta estimated over the previous 36 to 60 months, the low beta anomaly was present and resulted in an excess monthly return of 1.13% and was significant at the 10% level. When applying the Scholes-Williams methodology, the low beta excess return increased to 1.19% per month and was significant at the 5% level. However, the results of the Dimson beta portfolio sorts where paltry in comparison as the low beta excess return was only 0.18% month and insignificant.

The results of the dual independent sorts on momentum and beta presented above lack the finesse of quintile univariate sorts but add a dimension to the study of the low beta anomaly on the JSE. The momentum premium maintains a positive relationship with beta as the high beta momentum premium is significantly greater than its low beta counterpart. The driver of the relationship is largely due to high beta losers achieving significantly lower returns than low beta losers of the sample period.

The implication and potential addition to the minimal body of knowledge relating to the low beta anomaly is that the low beta premium seems largely confined to the historical loser stratum, implying that the low beta effect is not cross-sectionally consistent across shares listed on the JSE, which is a similar conclusion drawn by Gilbert, Strugnell and Kruger (2011). The authors conjectured that the inconsistent low beta premium is weak evidence in favour of low beta as an investment style and rather evidence in favour of the ineffectiveness of market beta describing the cross-sectional variation in share returns on the JSE. In terms of momentum, the results indicate that momentum is independent and not driven by the low beta anomaly.

4.3.2.2. Bivariate dependent sorts on momentum and market beta

The results presented above utilise independent portfolio sorts, where shares are stratified into terciles based on momentum and beta. In order to add further robustness and augment the tests of independence and interaction between beta and momentum, a dependent sorting methodology is applied where shares are initially sorted on momentum and weighted based on beta in order to achieve a natural tilt towards the low beta anomaly. The benefit of the dependent sorts are twofold. Firstly, quintile dependent sorts should provide superior (if not alternative) results to independent tercile sorts due to the refined concentration of momentum shares per portfolio, specifically in the extreme winner and loser portfolio sorts. Secondly, as discussed in the previous section, independent sorts on the universe of shares listed on the JSE may suffer from noise and industry bias due to a limited number of shares per portfolio, especially when applying price and liquidity filters. The small portfolio bias is potentially exacerbated by the additional requirement of shares requiring at least 36 months of prior returns for the purpose of estimated regressed proxies such as idiosyncratic risk and beta.

In order to replicate the effect of a dual sort on momentum and naturally weight towards the low beta anomaly, momentum shares are classified based on their six minus one month cumulative historical returns. Shares are sorted semi-annually into quintile portfolios based on their cross-sectionally defined historical momentum using 20th, 40th, 60th and 80th percentile breakpoints. In order to gain exposure to the low beta phenomenon, constituent shares (within the five momentum portfolios) are assigned weightings based on beta and the inverse of beta. High momentum (winner) constituent shares are assigned weights based on the inverse of beta while low momentum (loser) shares are assigned weights based on beta. The result is that the winner (loser) portfolio will naturally up weight (down weight) low beta shares and down weight (up weight) high beta shares. The results of the dynamically dependent style weighted momentum portfolios are then compared to momentum quintile portfolio sorts assuming equal and value (market capitalization) weighting. The dynamic style weighting is described mathematically as

$$W_i = \left(\frac{1}{\beta_i} \middle| P = 1,2,3\right) \qquad (4.18)$$

$$W_i = (\beta_i | P = 3,4,5) \qquad (4.19)$$

Where W_i represents the constituent weight of share i within one of the five momentum portfolios, β_i is the liquidity adjusted market beta for share i measured via time-series OLS regression using the J203 total return as the independent variable and P represents the

momentum portfolio where P1 is the extreme winner and P5 the extreme loser. Portfolio sorts are initiated from January 1997 and portfolio returns are calculated on a buy-and-hold basis where the total portfolio value is the sum of the cross-section of share weightings multiplied by their geometric returns at each point in time over the portfolio holding. The buy-and-hold methodology allows initial share weightings to vary through time, therefore accounting for each shares in-portfolio performance over the following six months in conjunction with its initial weighting. The results of the bivariate dependent sorts are expressed in the table that follows.

	P1	P2	P3	P4	P5	P1-P5
Mean Return	1.7548%	1.1575%	0.8709%	0.4094%	0.0445%	1.7103%
P-value	***0.0001******	***0.0028******	***0.0145****	***0.2719***	***0.9113***	***0.0001******
Sharpe	0.268	0.203	0.165	0.074	0.007	0.269
Treynor	0.023	0.021	0.012	0.006	0.001	1.768

*Table 4.15: Bivariate dependent sorts on momentum and liquidity adjusted beta. P-values are assigned asterisks based on statistical significance where *,**,*** indicate significance at the 10%, 5% and 1% level. All returns and performance statistics are based on monthly returns and risk measures.*

The results per Table 4.15 above depict the bivariate dependent sorts on liquidity adjusted beta and momentum measured over the previous six (less one) months. As mentioned, shares are initially sorted into quintiles based on momentum and then in-portfolio share weights are assigned in order to mimic the low beta anomaly. The results are largely consistent with those of the bivariate independent sorts (per Table 4.14) as the high momentum, low beta weighted portfolio (P1) achieves a monthly average return of 1.75% per month or 21% per annum and is significant at the 1% level.

Furthermore, portfolio returns decrease monotonically when moving across the momentum stratum and weighting towards higher market beta shares. Portfolio 5, which is long historical losers and weights shares based on market beta achieves the lowest return of 0.04% per month or 0.48% per annum and is not statistically different from zero. The excess return portfolio, which represents a long position in the historical winner/inverse beta weighted shares and a simultaneous short position in historical loser/beta weighted shares produces a monthly excess return of 1.71% per month or 20.52% per annum and is significant at the 1% level. Considering the additional risk metrics of the excess return portfolio, the Sharpe ratio indicates that the winner minus loser excess return produces 0.27% in average return for 1% in idiosyncratic risk borne. Most strikingly, the Treynor ratio of the excess return portfolio is the highest produced throughout the study thus far, where the ratio indicates that the excess return portfolio produces 1.77% of return per unit of market risk borne. The Treynor ratio of 1.77 can be directly related to the extraordinarily low beta of 0.009 of the excess return portfolio, which

is driven by the relatively low beta of the extreme winner portfolio (inverse beta weighted) and the relatively high beta of the extreme loser portfolio (beta weighted).

In order to determine the significance of the interaction between low beta phenomenon and momentum, the dynamically weighted low-beta momentum excess return portfolio is compared to quintile momentum sorts conducted over the identical sample period assuming equal and market capitalization weighting (as presented in tables 4.12(i) and 4.12(ii)). The purpose of comparison is to determine whether the dynamic style weighting methodology produces excess returns that differ to conventional weighting procedures used throughout literature and practice. A higher momentum premium implies that the style combination, through dynamic weighting, improves the momentum premium and therefore proves a positive interaction. Obviously, a lower premium would prove the inverse, indicating that the combination produces lower excess returns than equally and value-weighted momentum sorts, implying a relatively negative interaction between momentum and the secondary style. The comparative results are displayed in the table that follows.

	Low Beta Premium Weighted	Equally weighted	Value Weighted
Mean Return	1.7103%	1.5005%	1.5460%
P-value	***0.0001****	***0.0000****	***0.0000****
Sharpe	0.269	0.314	0.311
Treynor	1.768	0.117	0.116

*Table 4.16: Dynamic style weighted momentum versus equal and value weighted momentum premia. P-values are assigned asterisks based on statistical significance where *,**,*** indicate significance at the 10%, 5% and 1% level. All returns and performance statistics are based on monthly returns and risk measures.*

The results per Table 4.16 above indicate that the low beta weighted momentum premium exceeds that of the equally weighted and value weighted premium, producing 0.21% and 0.16% additional return per month, equivalent to 2.52% and 1.97% per annum. Interestingly, when considering risk metrics applied to the excess returns, on an idiosyncratic risk basis, the low beta weighted momentum premium underperforms its equally weighted and value weighted benchmarks, producing 0.27% per unit of idiosyncratic risk compared to 0.31% produced the equally and value weighted momentum premia. The relative underperformance is related to the relatively large monthly standard deviation of the low beta weighted momentum premium, which is 6.36%, compared to 4.77% and 4.97% achieved by the equal and value weighted momentum sorts respectively. Conversely, when adjusting for market risk, the low beta weighted momentum excess return achieves a Treynor ratio that is 15 times greater than both the equal and value weighted momentum premiums.

The result is largely driven by the effects of the weighting schematic. Throughout the study, high momentum (winner) portfolios tend to have a higher betas than their low momentum (loser) portfolio counterparts. The result of the dynamic weighting in order to mimic the low beta phenomenon is that the low beta momentum premium achieves a beta of 0.009 compared to 0.13 and 0.134 achieved by the equal and value weighted momentum premia over the sample period. The obvious result is that the Treynor ratio of the low beta weighted momentum excess return is superior with the significant difference being driven by market beta or denominator.

In conclusion, the results of the dependent sorts therefore indicate that there is a significant interaction between the momentum and low beta effect and that the combination of both strategies results in greater gross monthly and market risk adjusted returns over the equal and value weighted benchmarks. The excess return does seem to come at a price, as the low beta weighted momentum premium achieves a larger idiosyncratic risk that results in a Sharpe ratio lower than both the equal and value weighted momentum premiums. The results of the bivariate dependent sort are largely consistent with those of the bivariate independent sorts. Both find that momentum seems to maintain a positive relationship with the low beta anomaly on the cross-section of shares on the JSE. Notably, both sorts find that momentum is positive, significant and independent of the low beta anomaly on the JSE. In terms of the low beta phenomenon, the results of the independent sorts indicate that the low beta premium is largely concentrated in low momentum or loser shares.

The Independent sorts show that the momentum premium is highest in the high beta stratum, but that the result is largely driven by high beta loser shares. The lowest momentum premium is found in the low beta stratum and the poor result is attributable the positive performance of low beta loser shares. In order to optimally combine the low beta phenomenon with momentum, bivariate dependent sorts allowed for winner share to be weighted according to the inverse of beta while loser shares weighted based on market beta. The result of the dependent sort provided evidence of the positive interaction between anomalies, as the low beta weighted momentum excess return superseded those achieved by the equal and value weighted momentum excess return alternatives.

Finally, the dependent sorts in some sense provided stronger evidence in favour of the low beta anomaly, where the effect of the low beta weighting methodology provided the highest excess returns over the equal and value weighted benchmarks found in this study thus far. An obvious extension to the test of independence and interaction will be considered in the multivariate regression tests to follow in the preceding section.

4.3.3. Momentum and currency risk

The final the regressed factor considered is Rand or currency beta, which represents a shares relationship with the South African Dollar/Rand exchange rate. Comparatively, there is significantly less local and international literature on the topic of currency sensitivity driving share returns, specifically when compared to idiosyncratic risk and market beta. Currency risk is highly pertinent and topical for the following reasons. Firstly, the South African market, more specifically the JSE, has become a key destination for international funds attempting to gain exposure to emerging market returns. Secondly, a large proportion of the JSE, especially the larger market capitalization constituents, are dual listed and derive a large proportion of their operating profit from foreign markets. Since most papers that explore international factor or stylistic phenomena are currency neutral, with all returns converted to dollars, currency risk has largely been ignored as a potential determinant of the cross-sectional variation in share returns. The nature of the JSE and its constituents, each with various exposures to the local and foreign currencies, creates an avenue of research that has spurred interest in the investment community.

Burger and Warnock (2007) and Burnside, Eichenbaum and Rebelo (2001) found that the value of a local currency can proxy the overall well-being of an economy and may actually represent relative risk-aversion in foreign fund flows. In the seminal work of Barr and Kantor (2005), the authors considered the effects of currency risk on shares returns by evaluating the currency betas of the JSE top 40 shares based on market capitalization. Shares were classified into one of three categories (Rand Hedge, Rand Leverage and Rand Play) where the variation in rand betas was explained through operating revenues and expenses. Rand Hedge shares were deemed to have dollar denominated costs and revenues, Rand Leverage typically maintained dollar denominated revenues and rand denominated costs while Rand Play shares typically maintained rand denominated revenues and costs. The study considered the exchange rate betas of the Top 40 shares over the period January 2001 to August 2003, where exchange rate betas where measured as orthogonal to the JSE top 40 index using weekly data. The authors found that the rand betas strongly supported their classification scheme as shares with dollar denominated revenues and costs (Rand Hedge) produced positive exchange rate betas, implying that such shares experienced positive returns when the rand depreciated against the dollar. Rand Play shares produced significantly negative exchange rate betas, consistent with both their costs and revenues being locally denominated in Rands.

More recently, Page, Britten and Auret (2015) extended the work of Barr and Kantor (2005) by considering Rand Hedge as an investment style. The study furthered the findings of Barr and Kantor (2005) in one of three ways. Firstly, the entire cross-section of shares listed on the JSE over the period January 1996 to December 2013 was considered. Secondly, shares were sorted solely on their currency beta estimated assuming historical windows of between 36-60 months, without any *a priori* knowledge regarding the revenue and cost currency denominations. Lastly, in order to determine the investment plausibility of a Rand hedge strategy, shares were sorted into one of three portfolios (Rand Hedge, Rand Neutral and Rand Tracker) using a 33rd / 66th percentile split based on currency beta. Portfolios were formed on an annual basis and equally weighted geometric portfolio returns in excess of the equally weighted average of the universe of shares were estimated over the sample period. The authors found that portfolio returns increased monotonically when moving from Rand Hedge shares to Rand Tracker shares, where on a pure investment basis, Rand Hedge shares underperformed Rand Tracker shares by 0.472% per month with the difference just missing significance at the 10% level. The authors further noted that Rand Hedge shares produced the highest market beta and idiosyncratic risk, implying that neither market nor idiosyncratic risk could explain the poor performance (outperformance) of Rand Hedge (Rand Tracker) shares.

The results led to a secondary set of tests that attempted to define why Rand Tracker shares outperform Rand Hedge shares using a risk based framework. The authors intended to determine whether Rand Hedge shares truly hedge against currency fluctuations. If Rand Hedge shares mitigated currency exposure by being insensitive to drawdowns in the Rand, then under the assumption of risk and return, Rand Tracker shares should compensate investors for bearing currency risk. Using both time-series regressions and Vector Auto-Regressions, the authors found that Rand Hedge shares do indeed seem to guard against significant currency fluctuations in the Dollar/Rand exchange rate. Currency fluctuations were defined as extreme currency depreciations measured relative to a 12 month historical rolling window. In time-series regression tests, the Rand Hedge portfolio reacted positively to an extreme depreciation in the dollar Rand, increasing by 1.76% per month in such instances and was significant at the 1% level. Similarly, the Rand Tracker portfolio experienced significantly negative returns during extreme depreciations, losing 0.2% per month on average and was significant at the 10% level.

The results of the VAR impulse response functions and variance decomposition tests where similar to the results of the time-series regressions but lacked statistical significance, even though they portrayed the correct changes in portfolio values given a shock in the dollar Rand

exchange rate. The study therefore was the first to provide evidence relating currency risk to share returns. Notably, the following sections are the first, in terms of the current body of South African literature, to consider bivariate tests of momentum and currency risk, specifically in order to test whether currency risk is able to explain the momentum premium on the Johannesburg Stock Exchange. Therefore, both sets of bivariate sorts will firstly consider the independence and then interaction between currency risk and momentum.

4.3.3.1. Bivariate independent sorts on momentum and currency risk

The independent sorts on momentum and currency risk are virtually identical to those documented in the sections above where shares are sorted simultaneously into one of nine portfolios based on their six minus one month cumulative historical momentum (winner, medium and loser) and currency beta (rand hedge, rand neutral and rand tracker). At each portfolio sort date, shares are sorted based on momentum and currency beta separately using a 33rd / 66th percentile split. Prior to sorting, both a price and liquidity filter are applied where shares are required to have a current price in excess of 100 cents, cumulative zero daily trades (measured over the previous 12 months) less than 100 and achieve an average turnover in excess of the cross-sectionally estimated 10th percentile. In order to ensure unbiased currency beta estimates, shares further require a minimum number historical returns in excess of 36 months. Currency betas are estimated using time-series ordinary least squared regressions assuming a window period between 36 and 60 months, where the dependent and independent variables are the time-series share returns and changes in the dollar rand exchange rate. Unlike the estimations of market beta, no restriction is applied in terms of the R^2 of the regression estimate as the Rand neutral category generally contains shares with a non-significant relationship with the dollar Rand exchange rate with typically low R squared values. The time-series regression equation is best described via

$$Y_{i,t} = \alpha_i + \beta_{\$/ZAR}\Delta\$/ZAR + \varepsilon_{i,t} \qquad (4.20)$$

Where $Y_{i,t}$ represents the return on share i at time t, $\Delta_{\$/ZAR}$ is the monthly continuously compounded change in the US dollar Rand exchange rate and $\beta_{\$/ZAR}$ is the slope coefficient or exchange rate beta for share i measured over the previous 36 to 60 months. The methodology of Page, Britten and Auret (2015) is applied where shares are classified into one of three categories (expressed above) where rand hedge implies that the said share forms part of the upper 66th percentile, rand neutral shares achieve currency betas between the 33rd and 66th percentile and rand tracker in the bottom 33rd percentile. As per the independent sorts discussed above, portfolio returns are calculated on a buy-and-hold basis under the assumption of equal weighting at portfolio formation. Importantly, equal weighting is only

applied at portfolio initiation, after which constituent weights vary over the holding period until the next portfolio sorting date which is set to occur semi-annually. The results of the bivariate independent sorts are presented in the tables that follow.

	Winner	Medium	Loser	WML
Rand Hedge	1.5468%	0.5201%	-0.1288%	1.6757%
	0.0000***	***0.1238***	***0.7333***	***0.0000******
Rand Neutral	1.1984%	1.0670%	0.3898%	0.8086%
	0.0013***	***0.0009******	***0.3148***	***0.0140****
Rand Tracker	1.307%	0.986%	0.314%	0.993%
	0.0012***	***0.0062******	***0.4308***	***0.0022******
RHMRT	0.2394%	-0.4662%	-0.4432%	
	0.4753	**0.1639**	**0.1797**	

*Table 4.17: Portfolios sorted on six minus one month cumulative momentum and currency risk. P-values are assigned asterisks based on statistical significance where *,**,*** indicate significance at the 10%, 5% and 1% level. All returns and performance statistics are based on monthly returns and risk measures.*

The results per Table 4.17 show that the momentum premium is consistently positive and statistically significant, irrespective of currency risk stratum. Considering the momentum premia in the far right column, the momentum premium does not seem to maintain any distinct relationship with currency risk. The momentum premium is highest amongst rand hedge shares, where the excess return is 1.68% per month, equating to 20.11% per annum, and is significant at the 1% level. Similarly, the momentum premium achieved in the rand tracker stratum is 0.993% per month, equating to 11.92% per annum, and is also significant at the 1% level. The excess momentum returns do not seem to display any form of monotonic relationship with currency risk, however, the relationship that emerges is contrary to the findings of Page, Britten and Auret (2015) as the momentum premium is far stronger amongst rand hedge shares when compared to both the rand tracker and rand neutral stratum.

The rand hedge momentum premium exceeds the rand neutral and rand tracker momentum premium by 0.87% and 0.68% per month (equating to 10.5% and 8.2% per annum) respectively, with the former being significant at the 5% level and the latter just missing significance at the 10% level. The source of the relative outperformance, and the inconsistency with the findings of Page, Britten and Auret (2015), emanates from the extremely poor performance of the rand hedge loser shares compared to the likes of their rand neutral and rand tracker counterparts. Rand hedge loser shares achieve a negative monthly average return of -0.13% or -1.56% per annum, while rand tracker loser shares achieve gross monthly

returns of 0.314%, equating to 3.8% per annum. The difference between rand hedge and rand tracker loser shares is 0.443% per month or 5.32% per annum, but is statistically insignificant. When considering the difference in returns related to the long only winner portfolios, all returns are in excess of 1% per month and statistically significant at the 1% level irrespective of their currency risk.

Interestingly, rand hedge winner shares marginally outperform both rand neutral and tracker shares, achieving 1.57% per month compared to 1.2% and 1.3% respectively. The results therefore seem to indicate that the investment case described by Page, Britten and Auret (2015) is at odds with the findings, specifically in terms of the momentum premia and the performance of the long-only winner portfolios. Based on their findings, one would expect that rand tracker shares consistently outperform rand hedge shares, which is the case but only in the historical medium and loser momentum stratum. Considering the final row, which indicates the rand hedge minus rand tracker average monthly premium, rand hedge winners outperform rand tracker winners by 0.24% per month, equating to 2.9% per annum. A possible reason for the outperformance could be related to the underlying size (market capitalization) and liquidity of rand hedge shares in comparison to rand neutral and tracker shares. The current constituents of the top 40 shares listed on the JSE, and more specifically the top 10 shares based on market capitalization, are largely known to be rand hedge and rand neutral shares, deriving a large proportion of their revenues and expenses in non-ZAR currency.

Therefore, if a large proportion of rand hedge shares tend to have high relative market capitalizations and are highly liquid, then rand hedge share returns should be highly correlated with large market capitalization share returns. Similarly, smaller companies on the JSE, by their nature, maintain a greater relative proportion of rand denominated revenues and expenses. Referring to Table 4.1, large market capitalization winners outperformed small market capitalization winners by 0.11% per month. Similarly, Table 4.7 depicts that the high liquidity winner shares outperform low liquidity winners by 0.143% per month over the sample period. Therefore, it is possible that the relative outperformance of rand hedge shares over rand trackers is related to size and liquidity.

In order to test whether rand hedge shares are more likely to be large market capitalization shares, a dual sort is conducted on the cross section of shares used for the bivariate independent sort on momentum and currency risk, yet, the sort is now conducted on currency beta and market capitalization. The shares are sorted into one of three portfolios based on market capitalization and currency beta with the identical filters applied in terms of liquidity, price and historical number of data points. In order to determine the relative spread of market capitalization per currency risk stratum, the number of large capitalization shares per currency

beta portfolio are counted in each period and their time-series averages are calculated. The results are presented in the table below.

Currency Risk Portfolio	Average Number of Large Shares
Rand Hedge	31.68***
Rand Neutral	20.78**
Rand Tracker	5.62*
Difference (RH-RT)	**26.06*** **

*Table 4.18: Average number of large market capitalization shares per currency risk portfolio over the period January 1997 to June 2015. P-values are assigned asterisks based on statistical significance where *,**,*** indicate significance at the 10%, 5% and 1% level.*

The results presented above provide evidence in favour of rand hedge shares being highly correlated with large market capitalization liquid shares. The results indicate that the rand hedge portfolio on average contains 32 large market capitalization shares and is significant at the 1% level while the rand tracker portfolio only seems to have 6 large capitalization shares on average across the time-period and is significant at the 10% level. The difference in the average number of large market capitalization shares per the rand hedge and rand tracker portfolio is 26.06 and is significant at the 1% level. In order to relate the findings to the total number of shares per portfolio sort, the large market capitalization shares make 57% of the total portfolio constituents of the rand hedge portfolio on average, compared to only 5% of the constituents of the rand tracker portfolio. The test above can be criticised for being simplistic, however, the evidence is highly consistent with the assertion that rand hedge shares are generally larger capitalization, more liquid shares, thereby explaining the higher momentum premium being achieved by the rand hedge portfolio.

The results of the independent sorts on currency risk and momentum present a number of interesting findings. The momentum premium is independent of currency risk, as the momentum premium is consistently positive and significant, irrespective of the underlying currency risk of momentum shares. Importantly, the results of the interaction tests produces an inverse relationship to that which is described by the findings of Page, Britten and Auret (2015). The authors found, that on a pure investment basis, rand tracker shares outperform their rand hedge counterparts by 0.472% per month. The expected result would then be a positive interaction between momentum and currency risk, whereby the rand tracker momentum premium would exceed the rand hedge momentum premium, however the inverse is found. The result is largely driven by the marginal positive outperformance of rand hedge winners and extreme underperformance of the rand hedge losers. The potential cause of the inverse relationship is possibly attributable to the high correlation between rand hedge and

large market capitalization liquid shares, as the results of the dual sort on currency beta and market capitalization indicate that rand hedge shares are significantly more likely to be large capitalization shares when compared to rand neutral shares.

4.3.3.2. Bivariate dependent sorts on momentum and currency risk

Bivariate dependent sorts are conducted in order to provide further insight and robustness to tests of independence and interaction between momentum and currency risk. The benefit of dependent tests and, specifically the methodology to be applied, is that the independent three by three portfolio sorts, coupled with liquidity and price filters plus the addition of minimum historical data points may potentially result in small portfolio bias causing possible non-diversification and noisy returns. A further advantage is the increased concentration achieved through using quintile sorts as opposed to tercile portfolio breakpoints. The dependent sorting procedure applied initially sorts shares into one of five portfolios based on historical momentum assuming a six minus one month estimation period. The constituent shares in each portfolio are then weighted in order to mimic the expected currency risk effect. The results of the independent sorts are inconsistent with the findings of Page, Britten and Auret (2015) as the effect of combining currency risk with momentum results in rand hedge winner shares outperforming rand tracker winners from a long-only and excess return perspective.

In order to maintain consistency between the independent and dependent sorts, the dependent dual sorting methodology utilises in-portfolio weighting that up-weights rand hedge winner shares and down-weights loser rand tracker shares. Importantly, the weighting methodology applied to the dependent momentum/currency risk portfolio sorts is more complicated than the previous dynamic weighting mechanisms applied, as the currency betas range from being significant and highly positive (rand hedge) to significant and highly negative (rand tracker). In order to ensure an efficient weighting methodology that consistently up-weights rand hedge winners and down weights rand tracker losers but still maintains non-negative weightings in constituent shares, a methodology similar to Asness, Moskowitz and Pedersen (2013) is applied where shares are weighted based on relative rank.

As with the dependent sorts conducted above, shares are initially sorted on their historical six minus one cumulative returns. Shares are then assigned to one of five momentum portfolios and constituent shares are then ranked in ascending order according to currency beta. Each ranking is then scaled by the number of shares per portfolio (referred to as “scaled rank” hereafter) resulting in all constituent shares receiving a weighting between zero and one. The higher momentum portfolio constituent shares are weighted using the scaled rank while the lower momentum portfolio constituents are weighted using the inverse of the scaled rank. The

result is therefore that rand hedge winner shares within higher momentum portfolios receive higher relative weightings then their rand tracker counterparts. Conversely, rand tracker loser shares within the lower momentum portfolios receive higher weightings then their rand hedge counterparts. Formally, the dynamic weighting mechanism can be described mathematically via

$$W_i = (SR_i | P = 1,2,3) \tag{4.21}$$

$$W_i = \left(\frac{1}{SR_i} \middle| P = 3,4,5\right) \tag{4.22}$$

$$SR_i = \frac{Rank(\beta_{ZAR,i})}{n} \tag{4.23}$$

Where SR_i is the scaled rank of share i calculated as the in-portfolio ranking of share i based on currency beta scaled by the number of shares in the respective portfolio. Once again, P represents the respective momentum portfolio with P1 and P5 representing the extreme historical winners and losers respectively. In order to determine the degree of interaction, the dynamically weighted dependent portfolio sorts on momentum and currency risk are compared to identical momentum portfolios (i.e. identical share constituents) where returns are calculated assuming general and conventionally used value (market capitalization) and equal weighting. If the dynamically weighted methodology produces momentum excess returns greater (less) than that of the value and equally weighted momentum premium, one can conclude that the interaction between momentum and currency risk is positive (negative). The results of the bivariate dependent sorts are presented in the table below.

	P1	P2	P3	P4	P5	P1-P5
Mean Return	1.2972%	1.0607%	0.9305%	0.7299%	0.2515%	1.0456%
P-value	***0.0120*****	***0.0205*****	***0.0084******	***0.0481*****	***0.5162***	***0.0317*****
Sharpe	0.170	0.157	0.178	0.133	0.044	0.145
Treynor	0.016	0.014	0.013	0.011	0.004	0.112

*Table 4.19: Bivariate dependent sorts on momentum and currency risk. P-values are assigned asterisks based on statistical significance where *,**,*** indicate significance at the 10%, 5% and 1% level. All returns and performance statistics are based on monthly returns and risk measures.*

The results of the bivariate dependent sorts above indicate once again that momentum is independent of currency risk as momentum returns are significant and highly positive with the extreme winner portfolio producing the highest returns of 1.3% per month and is significant at the 5% level and the extreme loser achieves the lowest return of 0.25% per month and is statistically insignificant. Furthermore, portfolio returns decrease monotonically when moving

from the extreme winner to the extreme loser portfolios. The momentum premium achieved using the currency risk-weighting mechanism produces a monthly return of 1.05% and is significant at the 5% level. The results therefore irrefutably prove that momentum is independent of currency risk, however, they seem at odds with those of the independent sorts. Firstly, when compared to the other regressed factor sorts, the momentum premium is significantly lower, where the extreme winner portfolio produces a relative lower return (1.05% compared to 1.56% and 1.75% achieved by dependent sorts on idiosyncratic risk and beta), while the loser portfolio produces returns that are economically higher (0.25% compared to -0.13% and 0.04% per month).

The implication is therefore that the positive relationship between rand hedge and momentum may be somewhat driven by the tercile sorting methodology applied in independent sorts. Moreover, the dependant sort results may also provide weak evidence in favour of the findings of Page, Britten and Auret (2015). Due to the rand hedge dynamic dependent sort results being inconsistent with those of the independent sorts, the dependent sorts are re-conducted under the assumption of rand tracker shares providing a premium over rand hedge shares. Therefore, the dynamic weighting strategy will now up-weight winner rand tracker shares in the upper momentum portfolios and up-weight rand hedge loser shares in the lower momentum portfolios. The second weighting mechanism can therefore be expressed mathematically as

$$W_i = \left(\frac{1}{SR_i}\middle| P = 1,2,3\right) \tag{4.25}$$

$$W_i = (SR_i | P = 3,4,5) \tag{4.26}$$

$$SR_i = \frac{Rank(\beta_{ZAR,i})}{n} \tag{4.27}$$

The results of the second dependent sorts are presented in the table that follows.

	P1	P2	P3	P4	P5	P1-P5
Mean Return	1.6146%	1.0269%	0.6780%	0.8653%	0.0168%	1.5977%
P-value	***0.0001******	***0.0026******	***0.1111***	***0.0684****	***0.9695***	***0.0006******
Sharpe	0.266	0.204	0.107	0.123	0.003	0.233
Treynor	0.020	0.016	0.010	0.014	0.000	0.097

*Table 4.20: Bivariate dependent sorts on momentum and currency risk (rand tracker). P-values are assigned asterisks based on statistical significance where *,**,*** indicate significance at the 10%, 5% and 1% level. All returns and performance statistics are based on monthly returns and risk measures.*

The results presented in Table 4.20 provide evidence in favour of rand trackers producing higher absolute and risk adjusted returns when compared to rand hedge shares, consistent with the findings of Page, Britten and Auret (2015). Considering the results of the extreme winner portfolio, the effect of up-weighting rand tracker winner shares as opposed to rand hedge winners produces a monthly average return of 1.61% per month (19.4% per annum) and is significant at the 1% level. In comparison to the rand hedge weighted winner portfolio returns, the effect of rand tracker weighting adds 0.32% per month in additional return translating into 3.8% per annum. Similarly, considering the extreme loser portfolio, the effect of rand hedge weighting loser shares results in an insignificant average monthly return of 0.02% per month or 0.2% per annum compared to 0.25% per month achieved by the rand tracker weighted loser portfolio. The difference in portfolio returns is a statistically insignificant 0.23% per month. Economically, the difference in portfolio returns equates to rand tracker weighted loser shares earning 2.8% per annum on average in excess of rand hedge loser shares.

Considering the momentum excess return, the rand tracker weighting mechanism results in an average momentum premium of 1.6% per month and is significant at the 1% level. In comparison to the rand hedge momentum premium, rand tracker weighting results in additional monthly average excess monthly return of 0.55% per month, however the difference is not statistically significant. Economically however, the difference in the momentum premia translates into an additional 6.6% per annum on average that is solely driven through the weighting mechanism based on the findings of Page, Britten and Auret (2015).

As with the previous bivariate dependent sorts, the dynamic weighting methodologies are compared to conventional passive weighting mechanisms, specifically equal and value weighted quintile based momentum premia, calculated over the identical sample period and described in tables 4.12(i) and 4.12(ii). The results are presented in Table 4.21 that follows.

	Rand Tracker Weighted	Rand Hedge Weighted	Equally weighted	Value Weighted
Mean Return	1.5977%	1.0456%	1.5005%	1.5460%
P-value	***0.0006******	***0.0317****	***0.0000******	***0.0000******
Sharpe	0.233	0.145	0.314	0.311
Treynor	0.097	0.112	0.117	0.116

*Table 4.21: Rand Hedge dynamic style weighted momentum versus equal and value weighted momentum premia. P-values are assigned asterisks based on statistical significance where *,**,*** indicate significance at the 10%, 5% and 1% level. All returns and performance statistics are based on monthly returns and risk measures.*

The results displayed above clearly indicate the difference of rand tracker versus rand hedge weighted momentum excess returns, in relation to equal and value weighted momentum strategies. The rand tracker weighted returns are in excess of the equal and value weighted premia, resulting in additional average monthly returns of 0.1% and 0.05% (1.17% and 0.62% per annum) respectively. Conversely, the rand hedge weighted monthly excess return underperforms the equal and value weighted momentum premia by 0.45% and 0.5% per month, equivalent to 5.46% and 6% per annum. Interestingly, both the rand hedge and rand tracker momentum premiums produce lower risk-adjusted return metrics in comparison to their equal and value weighted counterparts. The equal and value weighted momentum premia produce Sharpe ratios of 0.31, while the rand tracker and rand hedge premium only produce 0.21% and 0.15% per unit of idiosyncratic risk respectively. Similarly, when adjusting for market risk, the rand tracker and rand hedge momentum premium produce Treynor measures of 0.10 and 0.11, compared to 0.12 achieved by both the equal and value weighted momentum premia respectively.

Focusing on the rand tracker weighted momentum premium, the main cause of the risk adjusted under performance emanates from the relatively higher idiosyncratic and market risk metrics. In terms of idiosyncratic risk, the monthly standard deviation of the equal and value weighted momentum premiums are 4.7% and 4.9% respectively. The rand tracker momentum premium achieved a monthly standard deviation of 6.9% thereby producing 44% and 38% more idiosyncratic risk relative to the equal and value weighted premiums. Similarly, the rand tracker momentum beta is 0.17, compared to 0.128 and 0.133 achieved by the equal and value weighted momentum premiums.

The results of the bivariate dependent sorts lead to different conclusions when compared to those garnered from the bivariate independent sorts. Using variations of the dynamic weighting strategy, the results prove that momentum does indeed maintain a positive relationship with currency risk, implying that rand tracker momentum returns exceed rand hedge momentum returns. In contrast to this, the independent sorts provided a diametrically opposite conclusion, showing that the rand hedge momentum premium outperformed the rand tracker momentum premium by a significant margin. Additional tests indicate that a possible cause of the outperformance is the high correlation between rand hedge and large market capitalization shares, implying that the three by three independent sort results may just be a masked version of momentums relationship with size and liquidity. Strengthening the concentration and power of the test through quintile sorts and dynamic weighting, the results of the dependent sorts conform to the findings of Page, Britten and Auret (2015), where the authors found that rand hedge shares underperform rand tracker shares on both a nominal

and risk-adjusted basis. Similarly, the dependent sort results show that momentum returns increase when weighting towards high currency risk shares, so much so that they outperform momentum equal and value weighted momentum premiums on a nominal basis. However, when allowing for risk adjustment, both the rand tracker and rand hedge dynamic weighting strategies underperform the equal and value weighted momentum premia, possibly suggesting that currency risk may be in some shape or form related to conventional measures risk, namely idiosyncratic risk and beta.

4.4. CHAPTER SUMMARY

The chapter extended the results presented in Chapter Three where momentum was found to be both significant and positive in univariate portfolio sorts. A natural extension to the testing of momentum is the inclusion of other variables within a bivariate test in order to determine whether momentum is truly an independent anomaly on the cross-section of shares listed in the Johannesburg Stock Exchange. A corollary to the test of independence is the identification of interaction between momentum and the various stylistic anomalies considered in the chapter. The popularised anomalies considered in the chapter are split into two distinct groups, the first considering historically popular anomalies such as size, value and liquidity while the second considers regressed factors such as beta, idiosyncratic risk and currency risk. In order to improve the power and robustness of the results, two portfolio sorting methodologies are applied. The first methodology is independent bivariate sorts where shares are sorted into one of nine portfolios based on momentum and the non-momentum anomaly. The second methodology applied is the bivariate dependent sorts, where shares are initially sorted into quintile portfolios based on momentum and then dynamically weighted in order to mimic the none-momentum anomaly. The results of the chapter are summarised in the paragraphs that follow.

The first pricing anomaly considered is the size premium of Banz (1981). The results indicate that momentum premium on the JSE is not explained by the size effect. The results of the bivariate independent sorts show that the momentum premium is independent of size as the momentum premium is significantly positive, irrespective of the size tercile. Interestingly, the highest momentum excess return was found in the medium market capitalization tercile, achieving a significantly positive excess return of 0.89% per month on average. The dependent dynamic weighting results however indicated that there is a marginally positive interaction between momentum and the size premium (and therefore a negative relationship with size) as the size premium weighted momentum excess return is marginally higher than the equal and value weighted momentum premium over the time-period. The relationship is at

best weak as the size premium weighted excess return achieves an additional return of 17 and 15 basis points per month over the equally weighted and value weighted momentum premiums respectively. Lastly, the results of the bivariate sorts are consistent with the findings of Auret and Cline (2011) and more recently Page, Britten and Auret (2016) as the findings in table 4.1 indicate that the size premium has largely dissipated on the JSE.

The second pricing anomaly considered is the value premium of Basu (1977). The results of the independent sorts are largely consistent with the findings of Asness (1997) and Asness *et al.* (2013) as momentum seems to display a significantly negative relationship with the value premium. The results indicate that the momentum premium is not present in the high value tercile but increases monotonically and is largest in the growth tercile. The findings are virtually identical for the value premium, where the value effect is non-existent in the winner tercile but increases and is largest in the extreme loser tercile. Interestingly, the source of the interaction is largely driven by the short positions in the zero cost strategies or excess return premiums. The source of the non-existent momentum premium in the value tercile is caused by the relatively superior performance of the value loser portfolio, where the said portfolio achieves a significant return of 1.062% per month. Interestingly, on a long-only basis, the highest return is achieved by the high value winner portfolio, earning 1.48% per month implying a positive interaction between value and momentum on a long-only basis. The results of the dynamic weighting sorts confirm the results of the independent bivariate sorts where the value premium weighted momentum excess return underperforms the market capitalization and equal weighted quintile zero costs momentum premiums, implying that value and momentum maintain a significantly negative relationship on the JSE.

The third non-momentum style considered is the liquidity effect of Amihud and Mendelson (1986). The results of the bivariate independent sorts are unique as the momentum premium seems to display a negative relationship with liquidity, consistent with the notion of a typical liquidity premium, however, there does not seem to be any consistent liquidity premium on the JSE. The results are largely driven by the short position in the liquid and illiquid loser portfolio. The highly liquid loser portfolio achieves a monthly return of 0.726% per month and just misses significance at the 10% level, while the low liquidity loser portfolio achieves a monthly return of just 0.116% per month. The variation in loser portfolios returns amounts to a significant momentum premium in the low liquidity tercile that achieves an additional 5.6% per annum over the sample period. Interestingly, the findings of the dependent sorts are inconsistent with the those of the bivariate independent sorts as the dynamically weighted inverse liquidity premium momentum portfolios (that up-weight liquid winners and illiquid losers) achieves an excess momentum premium of 1.78% per month, beating both the equivalent equally and

value weighted momentum premiums by 2.93% and 2.92% per annum respectively. The results of the dependent sorts are therefore consistent with the findings of Page, Britten and Auret (2013) where the authors found that the momentum premium on the JSE maintains a positive relationship with liquidity, consistent with the behavioural 'herding' explanation of the inter-causal relationship between momentum and liquidity.

The first of the regressed style proxies considered is idiosyncratic risk, measured as orthogonal to the J203 ALSI. The independent sorts on momentum and idiosyncratic risk indicate a positive relationship between momentum and idiosyncratic risk, proving inconsistent with the findings of McLean (2010) and Page, Britten and Auret (2016) as both studies found that the limits to arbitrage hypothesis fails to explain the momentum premium. The findings are however consistent with Conrad and Kaul (1998) as the authors found that cross-sectional dispersion will result in greater momentum profits. The results of the dependent dynamic weighting quintile portfolio sorts are however inconsistent with the results of the independent sorts as the dynamic weighting methodology that up-weights low volatility winners within the winner portfolio and similarly up-weights high volatility losers produces a higher momentum premium than a simple equal and value weighted approach. The low-volatility weighted momentum premium achieves an excess monthly mean return of 1.69% per month, providing 2.31% and 1.76% additional profit per annum over the equal and value weighted momentum premium respectively.

The low beta anomaly of Frazinni and Pedersen (2013) is then explored where shares are sorted based on momentum and liquidity adjusted beta. The independent sorts indicate that the momentum premium is independent of the low beta anomaly but does seem to maintain a negative interaction with beta (and therefore a positive interaction with low beta). The low beta momentum premium is 1.788% per month while the high beta momentum premium achieved 0.698% per month. The difference in premiums amounts 1.09% per month and is Signiant at the 1% level. The positive interaction is further strengthened by the dependent dynamically weighted portfolio sorts. The low beta momentum premium produces 2.52% and 1.97% additional profit over the equal and value weighted momentum sorts, further proving a positive interaction between the low beta anomaly and the momentum premium.

The final pricing anomaly considered is South Africa specific and considers currency risk as described by Barr and Kantor (2005) and more recently, Page, Britten and Auret (2015). The results of the independent sorts indicate that the momentum premium on the JSE seems to be independent of currency risk, as irrespective of currency risk stratum, the momentum premium is positive and significant. Interestingly, the results indicated that the momentum premium is highest in the rand hedge stratum, achieving an excess momentum return of

1.68% per month and is significant at the 1% level. The results are inconsistent with the findings of Page, Britten and Auret (2015) as the authors found that rand tracker shares out performed rand hedge shares on the JSE. However, the results can be related to the positive interaction between momentum, size and liquidity as the rand hedge portfolio was found to comprise mostly of large market capitalization shares, potentially driving the interaction between currency risk and momentum. The dependent dynamically weighted portfolio sorts provided results that are inconsistent with the independent sort findings but consistent with the findings of Page, Britten and Auret (2015) as the rand tracker weighted momentum premium exceeded the value and equally weighted premiums. Moreover, the rand hedge momentum premium significantly underperformed the value and equally weighted premiums by 5.46% and 5.99% per annum respectively.

The bivariate tests of momentum provide a plethora of evidence in favour of the presence of a consistent positive premium produced by momentum on the JSE on both a long-only and long-short basis. The results are both unique and novel in terms of applying two sorting methodologies that definitively strengthen the power of the test and robustness of the findings. The findings of the chapter significantly augment the body of literature related to momentum and other pricing anomalies on the JSE. Furthermore, the findings are unique to the South African literature as, to the best of the authors' knowledge, there is no explicit tests of the low volatility and beta premium on the JSE. Similarly, the set of tests and variables considered is the most thorough test of the momentum premium on the JSE, providing significant insight to the intricacies of the momentum premium on the JSE, its interaction with other none momentum styles and the benefit (detriment) of combining strategies (anomalies) on the JSE. Unfortunately, bivariate sorts are a limited test as the extension to include more variables is not feasible given the restricted investable universe of shares listed on the JSE. In order to increase the scope, power and potential parameters applied to the test of momentum on the JSE, multivariate time-series attribution regressions are to be conducted in the following chapter, in order to determine in a multivariate setting whether noted factors are able to explain the momentum premium on the cross-section of shares listed on the JSE.

CHAPTER FIVE: TIME-SERIES REGRESSION TESTS OF MOMENTUM

5.1 INTRODUCTION

The prior two chapters considered univariate and bivariate tests of momentum on the cross-section of shares listed on the JSE. The commonality between Chapters Three and Four is that both scrutinized momentum returns using non-linear, unconstrained tests in order to test whether momentum exists, achieves significantly positive excess returns and most importantly, whether momentum is independent of other noted investment strategies that are present on the cross-section of shares listed on the JSE. The natural logical progression of the test is the extension of bivariate tests to a multivariate setting, thereby applying numerous potential explanatory factors in a single linear test. The chapter that follows intends to determine whether various independent variables are able to explain the momentum premium and provide insight into the dynamics of the momentum premium by firstly analyzing the variation in time-series alphas produced in regression results and further considering the factor exposures/loadings that explain or drive the momentum premium on the JSE. The section that follows details the methodology in terms of portfolio sorts, independent variables and time-series regression tests to be applied.

5.2 METHODOLOGY

Like the previous chapters, portfolio sorts are conducted on the cross-section of shares listed on the JSE. The sample period considered spans from 1 January 1992 to 30 June 2015, yet the portfolio initiation date is set to 1 January 1997 in order to allow a sixty month period for portfolio sorting procedures that utilize regressed proxies, specifically market beta, idiosyncratic risk and currency risk. Univariate quintile sorts are conducted using the following style based investment criteria; momentum proxied by historical cumulative return measured over the previous six minus one months, value proxied by the median book-to-market ratio, size proxied by the natural logarithm of market capitalization, market beta measured using OLS regression on the J203 ALSI, idiosyncratic risk, measured as orthogonal to the J203 ALSI and currency risk proxied by the OLS coefficient measured against changes in the dollar/Rand exchange rate.

Once again, in conducting quintile portfolio sorts, uniform liquidity and transaction cost filters are applied where at each portfolio sort date, shares are excluded if they achieve more than 100 zero daily trades over the previous year, maintain an average turnover ratio (share volume scaled by number of shares in issue) in the cross-sectionally defined bottom 15th percentile and have a share price less than 100 cents. Additionally, shares are required to have been

listed for 12 months prior to portfolio formation. All portfolio sorts (barring momentum) are conducted on a semi-annual basis where equally weighted quintile portfolio returns are calculated assuming buy-and-hold as opposed to constant reweighting during portfolio holding periods. Momentum sorts are conducted assuming three differing weighting mechanisms, where returns are calculated assuming equal weighting, market capitalization weighting and momentum weighting. The momentum weighting methodology is similar to that applied by Asness *et al.* (2013) where shares are sorted initially on momentum and then assigned weights based on the relative cross-sectional momentum rank, resulting in high momentum shares having higher weights in the upper quintile (winner) portfolios and the lower momentum shares being up-weighted in the lower momentum (loser) quintile portfolios. As noted in Chapter Three and Four, if a share delists over the portfolio holding period, the share is assigned a penalty return of -100%.

The time-series regressions to be conducted are common across asset pricing and investment literature, where the dependent variable is the investment 'style' in question and the independent variables are either market premium proxies or excess returns (factor premia) produced by other noted stylistic investment strategies. The basis of the time-series regression tests is rooted in portfolio mathematics and econometrics common to asset pricing literature. The tests originate from the initial tests utilized to define asset pricing models and tests of the CAPM, but have morphed into attribution tests that attempt to define risk-adjusted excess returns as well as providing a linear risk-based equilibrium pricing explanation for the existence of mispricing. Importantly, it should be stressed that the tests that follow are specifically not asset pricing tests, but rather attribution tests that intend to determine whether noted factor premia can explain the momentum premium on the JSE and whether the momentum premium exists in a multi-factor setting. Formally, the tests considered can be summarized by the basic mathematical form

$$R_{i,t} - r_f = \alpha_i + \sum_{j=1}^{L} \beta_{i,j} X_{j,t} + \varepsilon_{i,t} \qquad (5.1)$$

Where $R_{i,t}$ is the momentum portfolio i return at time t, r_f is the 90 day treasury bill rate, α_i is the time-series alpha representing the excess risk-adjusted return earned by portfolio i, β_i is an L x 1 vector of time-series factor loadings, $X_{j,t}$ represents a T x L matrix of L excess return premia and $\varepsilon_{i,t}$ the time-series error term that is assumed to be homoscedastic, stationary and follows a normal distribution ($\varepsilon \sim N(0, \sigma^2)$). The basic regression test above will be conducted allowing for variation in the assumptions related to momentum weightings and varying sets of explanatory independent variables that have been commonly used to explain the cross-

sectional variation in share returns. The first attribution model is based on the CAPM, where the sole explanatory independent variable is the returns of JSE ALSI in excess of the 90 day T-bill rate. The second attribution model will utilize the popularized Fama and French (1992,1993 and 1995) factors, using the excess returns on the JSE ALSI, excess returns of the highest value portfolio less the lowest (value minus growth) and the excess returns on the small capitalization minus large market capitalization portfolio (small minus big). The next model is effectively a 'ad-hoc' model unique to the literature that will incorporate the low beta, low idiosyncratic risk, currency beta and liquidity premium by utilizing the excess returns on the low minus high beta, low minus high idiosyncratic risk, rand hedge minus rand tracker and high liquidity minus low liquidity time-series excess returns. The justification of applying such a model is that a number of the factors considered are relatively new and may provide additional explanatory power when attempting to explain the momentum premium. The final attribution model considered utilizes the factors espoused by van Rensburg (2002) where the author found that the JSE Financial-Industrial Index (FINDI) and JSE Resources Index (RESI) can be used as observable proxies of the first two principal components able to explain the cross-sectional variation in share returns listed on the JSE. The four models considered can be expressed as

$$R_{i,t} - r_f = \alpha_i + \beta_{i,J203} RMRF + \varepsilon_{i,t} \tag{5.2}$$

$$R_{i,t} - r_f = \alpha_i + \beta_{i,J203} RMRF + \beta_{i,size} SMB + \beta_{i,value} VMG + \varepsilon_{i,t} \tag{5.3}$$

$$R_{i,t} - r_f = \alpha_i + \beta_{i,J203} RMRF + \beta_{i,lowbeta} LBMHB + \beta_{i,idio} LIMHI + \beta_{i,ZAR} RTMRH + \beta_{i,LIQ} HLMLL + \varepsilon_{i,t} \tag{5.4}$$

$$R_{i,t} - r_f = \alpha_i + \beta_{i,findi}\left(FINDI - r_f\right) + \beta_{i,resi}\left(RESI - r_f\right) + \varepsilon_{i,t} \tag{5.5}$$

The focus of the tests will be determining the magnitude, significance and economic meaning of the time-series alphas, as well as the specific factor loadings that explain momentum returns. Alphas will also be formally tested using the GRS statistic of Gibbons, Ross and Shanken (1989) which is a finite sample F-test with the null hypothesis that all time-series alphas estimated using the various momentum test portfolios are jointly equal to zero. Due to the central importance of the results related to the GRS statistic and its implication on the presence and consistency of momentum (within this chapter), the implications and background of the GRS statistic are discussed further.

In their seminal work, Gibbons, Ross and Shanken (1989) developed a viable test for determining the efficiency of the market portfolio in response to the assertions of Roll (1977) who stated that all tests of the CAPM are flawed in that none use a true market proxy. Roll (1977) in fact went on to create an empirical impasse as the conclusion of the study implied that the CAPM cannot be tested as there is no means of determining the true market portfolio and by extension, the true efficient frontier. In response to the empirical conundrum, Gibbons, Ross and Shanken (1989) developed a logical test of ex-ante efficiency by considering the joint consistency of time-series alphas. The basic test considers all test portfolio (i) alphas

$$R_{i,t} - r_f = \alpha_i + \sum_{j=1}^{L} \beta_{i,j} X_{j,t} + \varepsilon_{i,t} \qquad \forall_i = 1,2 \dots \dots N \qquad (5.6)$$

And tests the hypothesis that all alphas are jointly equal to zero. Formally the null and alternative take the form

$$H_0: \alpha_i = 0 \qquad \forall_i = 1,2 \dots \dots N \qquad (5.7)$$

$$H_A: \alpha_i \neq 0 \qquad \forall_i = 1,2 \dots \dots N \qquad (5.8)$$

Under the null, the market proxy is ex-ante efficient as all alphas are jointly equal to zero, implying that the assumed market proxy successfully explains the variation in test-portfolio returns and therefore plots on the efficient frontier. The alternative hypothesis posits one of two possibilities, the first being that the underlying risk premia (and therefore pricing model) is not efficient **or** that the current risk framework model fails to capture the variation in the test portfolio returns. The test can be formally defined mathematically via

$$\left(\frac{T}{N}\right)\left(\frac{T-N-L}{T-L-1}\right)\left[\frac{\hat{\alpha}'\widehat{\Sigma^{-1}}\hat{\alpha}}{1+\widehat{\mu}'\,\Omega^{-1}\,\hat{\mu}}\right] \sim F(N, T-N-L) \qquad (5.9)$$

Where T is the number of time-series returns, N is the number of test portfolios, L is the number of independent time-series excess return factor premia used to describe the test portfolio returns, α_i is an N x 1 vector of estimated intercepts, Σ is the variance covariance matrix estimated using the test portfolio residuals, μ is an L x 1 vector of sample means and Ω is an L x L variance-covariance matrix estimated using the L factors under the assumption that alphas follow an non-central F distribution with degrees of freedom N and (T-N-L). For the purposes of this chapter, the application of the GRS statistic is applied to determine whether excess returns achieved by a momentum strategy applied on the cross-section of shares listed on the JSE can be explained by L factor premia. Therefore, the sections that follow will

explicitly apply both time-series regressions coupled with the GRS statistic in order to determine whether the four models considered successfully explain the variations of the momentum premium on the JSE. Notably, the number of time series regressions to be conducted amounts to number of momentum portfolios (5) estimated using three weighting procedures (3) multiplied by the number attribution models (4) considered, implying in total 60 (5 x 3 x 4 = 60) time series regressions. Appendix 1a contains all the necessary pre-tests related to the underlying data necessary to carry out time-series regressions, specifically sample statistics, univariate factor results, correlation matrices and univariate and joint tests of stationarity. Lastly, all time-series regressions are estimated using Newey-West HAC consistent standard errors in order to mitigate the potential heteroskedasticity and serial-correlation commonly noted in economic/financial econometric literature.

Lastly, it should be reiterated that three weighting mechanisms are applied to the momentum quintile sorts. The purpose of the variation is to identify whether, on a risk-adjusted basis, momentum in three different forms achieves significant excess returns. Additionally, the methodological differences will also provide insight into the dynamics of momentum and its sensitivity to weighting dynamics in a multivariate linear scenario. The weighting mechanisms are relatively simple when compared to the dynamic weighting schematics applied in Chapter four, however, the simplicity of the weighting schematics will potentially provide important information in terms of the optimal risk-adjusted momentum premium and possibly the incremental benefit (or pitfall) of the weighting schematic assumed when applying a momentum strategy on the cross-section of shares listed on the JSE.

5.3 TIME-SERIES TESTS OF MOMENTUM USING THE MARKET MODEL (CAPM) SPECIFICATION

As mentioned, the first time-series regression tests to be conducted will rely solely on the excess return achieved on the JSE ALSI over the sample period, implying attribution regressions applied against the equal, market capitalization and momentum weighted quintile momentum test portfolios. The basic model applied can be directly related to the market model or CAPM via

$$R_{i,t} - r_f = \alpha_i + \beta_{i,J203} RMRF + \varepsilon_{i,t}$$

Where both the momentum test portfolio and the J203 index total return (adjusted for corporate actions such as dividends, share splits, consolidations and unbundling's) are measured in excess of the 90 day T-bill rate over the sample period. The results of the time-series

regressions are presented in the tables that follow where each table separately presents results of the three variations in weighting applied to the momentum test portfolios respectively

	Momentum - Equal Weighting		
	α	β_{J203}	Adj. R^2
1	0.0053	0.8582	61.33%
	0.0416*	***0.0000******	
2	-0.0006	0.6572	57.80%
	0.7877	***0.0000******	
3	-0.0029	0.7007	61.03%
	0.1724	***0.0000******	
4	-0.0044	0.6686	53.17%
	0.0655*	***0.0000******	
5	-0.0095	0.7242	56.09%
	0.0001***	***0.0000******	
1-5	0.0148	0.1340	2.45%
	0.0001***	***0.1528***	
GRS	4.7321		
	0.0000***		

*Table 5.1 Time-series regression results conducted on equally weighted momentum test. P-values are assigned asterisks based on statistical significance where *,**,*** indicate significance at the 10%, 5% and 1% level.*

The results of the time-series regressions depict the presence of a significant risk-adjusted momentum premium present on the cross-section of shares listed on the JSE. The second column depicts the time-series alphas of the regressions where, as expected, the highest momentum portfolio (Portfolio1) achieves the highest alpha, equivalent to 0.53% per month or 6.3% per annum and is significantly different from zero at the 5% level. The highest momentum portfolio also seems to achieve the highest market loading, achieving a market beta of 0.86 and is significant at the 1% level. Consistent with the results presented in Chapters Three and Four, momentum alphas decrease monotonically, going from being significantly positive to significantly negative when moving from the extreme winner to the extreme loser portfolio. The extreme loser portfolio achieves a monthly alpha of -0.95% per month, equating to average loss of -11.41% per annum and is significant at the 1% level.

Consistent with the findings of Jegadeesh and Titman (1993, 2001), the extreme loser portfolio produces the second highest market loading (beta) of 0.724 and is significant at the 1% level[12].

[12] Importantly, it is notable that the time-series market betas are below unity on average. Upon investigation, the main cause of non-unity is twofold. Firstly, the application of the 100% penalty return applied when shares delist significantly deviates portfolio

The second last row presents the results of the equally weighted momentum excess returns regressed on the JSE ALSI market proxy. The zero cost long-short portfolio achieves a monthly excess return of 1.48%, equivalent to 17.7% per annum, and is significant at the 1% level. The excess return portfolio effectively represents the pure equally weighted momentum factor, and as expected, produces an insignificant market loading of 0.13 and an adjusted R^2 of 2.45%. The results imply that momentum on the JSE, assuming equally weighted portfolio returns, produces a significantly positive premium that cannot be explained by market risk nor the CAPM. Such a deduction is natural as the risk adjusted portfolio returns (alpha) experience significant variation that is not related to market risk or beta. Lastly, the GRS statistic is calculated using an F-distribution assuming F~ (5,219). The GRS statistic equals 4.732 and results in a rejection the null hypothesis of the momentum alphas being jointly equal to zero at the 1% level of significance. The result of the GRS test provides further evidence negating the ability of the conventional market model or CAPM explaining the significant outperformance achieved by the momentum premium on the JSE.

	Momentum - Market Capitalization Weighting		
	α	β_{J203}	Adj. R^2
1	0.0061	0.8858	63.93%
	0.0152***	***0.0000******	
2	-0.0002	0.6783	61.49%
	0.9503	***0.0000******	
3	-0.0023	0.7242	65.10%
	0.2539	***0.0000******	
4	-0.0039	0.6944	55.54%
	0.0933*	***0.0000******	
5	-0.0094	0.7518	57.90%
	0.0007***	***0.0000******	
1-5	0.0155	0.1340	1.84%
	0.0001***	***0.1676***	
GRS	4.6721		
	0.0000***		

*Table 5.2 Time-series regression results conducted on market capitalization weighted momentum test portfolios. P-values are assigned asterisks based on statistical significance where *,**,*** indicate significance at the 10%, 5% and 1% level.*

returns from those of the market. Secondly, and more importantly, the reinvestment horizon applied is six months compared to the reweighting of the J203, which occurs daily. A set of simulations were run where portfolio holding periods are set to three months and no penalty return is applied. The time-series CAPM regressions produced betas that where just above and below 1 while alphas were significantly higher than those described in Table 5.1.

Table 5.2 depicts the time-series regression results of the market capitalization weighted momentum portfolios. Consistent with the results portrayed in Table 5.1, time-series alphas decrease monotonically when moving from the extreme winner test portfolio (portfolio 1) to the extreme loser (portfolio 5). The market capitalization weighted extreme winner portfolio achieves a time-series alpha of 0.61% per month, equating to 7.3% per annum and is significant at the 5% level. The extreme winner portfolio also realizes the highest market factor loading, achieving a market beta of 0.89 and is significant at the 1% level. The market capitalization weighted extreme loser portfolio produces an average monthly loss of -0.94%, equating to an annualized average loss of -11.26% and is significant at the 1% level. The zero cost momentum premium, presented in the final row of the table, indicates a risk-adjusted market capitalization weighted momentum premium of 1.55% per month, equivalent to 18.58% per annum and is significant at the 1% level.

Interestingly, when comparing the results of Tables 5.1 and 5.2, the market capitalization weighted momentum portfolios dominate their equivalent equal weighted counterpart in terms of alpha and market loadings. Considering the extreme winner portfolios, the market capitalization weighted winner alpha exceeds the equal weighted by 0.084% per month, equating to a full 1% per annum on average. Similarly, the market capitalization weighted loser portfolio achieves a marginally higher return of -0.94% compared to -0.95% average loss per month of the equally weighted loser portfolio. The difference in time-series alpha culminates in the market capitalization weighted momentum premium being approximately 0.07% higher per month (0.87% per annum) on average. Similarly, the market betas (factor loadings) are higher for the market weighted momentum portfolios but follow the same general pattern as that of their equally weighted counterparts. The results thus far are inconsistent with the findings of Lewellen (2002), Korajczyk and Sadka (2004), Basiewicz and Auret (2009) and the findings described in Chapter Three as, on a risk-adjusted basis, momentum profits seem to maintain a positive relationship with market capitalization. The results do however conform to those of McLean (2010) and Auret and Cline (2011) as McLean (2010) found that momentum profits increased when assuming value (market capitalization) weighting, while Auret and Cline (2011) found that the size premium has largely disappeared in the cross-section of shares listed on the JSE. A possible explanation for the market weighted outperformance could be related to the disappearing size effect where large market capitalization shares are largely outperforming medium and small capitalization shares.

A second possible explanation could be that market capitalization weighting natural up-weights portfolio constituents that are larger and relatively more liquid than their small counterparts. Therefore, the additional risk-adjusted return may be related momentum having

a positive relationship with liquidity as expressed by Hameed and Kusnadi (2002) and Page, Britten and Auret (2013). The explanation behind the higher market factor weightings (market betas) is more straightforward as the market proxy (J203) applied is a value-weighted index, implying that market weighting returns should generally result in larger betas. Barring the mild discrepancy in risk-adjusted returns, an identical pattern emerges from the market capitalization weighted results. Momentum profits are significant and positive on a risk-adjusted basis and cannot be explained by the CAPM. Evidence of the fact can be directly read from the significant discrepancy in portfolio alphas that is not matched by their market factor loadings, with market betas being relatively flat across the portfolio sorts. Lastly, the GRS statistic (4.672) results in a rejection of the null hypothesis at the 1% level of significance indicating that the time-series alphas of the market capitalization weighted momentum portfolios are jointly not equal to zero. The GRS test therefore provides further confirmation that the CAPM (market model) specification fails to explain the momentum premium on the cross-section of shares listed on the JSE.

The final weighting specification used applies a variant of the weighted relative strength strategy ("WRSS") weighting methodology developed by Lo and Mackinlay (1990) and popularized by Lewellen (2002) and Jegadeesh and Titman (2002). More recently, Asness, Moskowitz and Pedersen (2013) utilized a weighting methodology based on relative strength, therefore weighting based on historical momentum, but instead of using the actual cumulative returns as initial portfolio weights, the authors used a scaled rank based on cumulative momentum earned over the momentum estimation period. Like Asness *et al.* (2013), a similar WRSS methodology is applied based on the shares relative momentum rank measured over the previous six minus one month. The natural result of the momentum rank weighting is that the highest momentum shares within the winner portfolios, i.e. portfolios 1 and 2, achieve the highest initial portfolio weighting while the inverse is applied to the extreme loser shares in the lower momentum quartiles, i.e. portfolios 4 and 5, where shares with the worst performance are assigned the highest weights. The results of the momentum rank weighted quartile portfolios are displayed in Table 5.3 that follows.

	Momentum - Momentum Rank Weighting		
	α	β_{J203}	Adj. R^2
1	0.0063	0.9539	33.92%
	0.2069	***0.0000****	
2	-0.0008	0.6544	56.71%
	0.7076	***0.0000****	
3	-0.0030	0.6955	60.31%
	0.2391	***0.0000****	
4	-0.0044	0.6715	53.08%
	0.1383	***0.0000****	
5	-0.0099	0.7267	55.60%
	0.0001*	***0.0000****	
5-1	0.0162	0.2272	2.08%
	0.0026*	***0.0172****	
GRS	3.5579		
	0.0081*		

*Table 5.3 Time-series regression results conducted on momentum rank weighted momentum test portfolios. P-values are assigned asterisks based on statistical significance where *,**,*** indicate significance at the 10%, 5% and 1% level.*

The results of the momentum rank weighted quintile test portfolios conform to the findings presented in Tables 5.1 and 5.2. Once again, the time-series alphas of the test portfolios decrease monotonically when moving from the extreme winner to extreme loser quintiles. The extreme winner portfolio produces an alpha of 0.63% per month, equating to 7.55% per annum but lacks statistical significance. In comparison to the equal and value weighted momentum portfolio results, the momentum rank weighted winner portfolios alpha is economically higher, delivering 0.3% and 0.2% more risk-adjusted return per annum respectively, but is the only extreme winner portfolio alpha that lacks statistical significance. Additionally, the market loading of the extreme winner portfolio is economically higher than both the equal weighted and value weighted extreme winner market betas, delivering a market beta of 0.954 compared to 0.86 and 0.89 respectively.

The momentum rank weighted extreme loser portfolio realizes a time-series alpha of -0.99%, presenting the highest risk-adjusted loss of the three weighting methodologies. Barring the insignificance of the extreme winner risk-adjusted return, the momentum premium achieved by the momentum rank weighted momentum portfolios is 1.62% per month, equating to 19.4% per annum and is significant at the 1% level. The results therefore indicate that the momentum rank weighted momentum premium delivers the highest excess return premium, exceeding the equally and value weighted momentum premiums by 1.71% and 0.81% per annum

respectively. Most interestingly, the significance and magnitude of the extreme winner portfolio beta results in the momentum rank weighted premium being the only momentum premium to achieve a statistically significant (at the 5% level) beta of 0.23. Lastly, the GRS statistic value achieved using the momentum rank weighted momentum test portfolios is 3.56, resulting in a rejection of the null hypothesis at the 1% level that test portfolio alphas are jointly equal to zero.

The results of the momentum rank weighted portfolio time-series regressions provide evidence consistent with the results of the equal and value weighted momentum sorts. Firstly, the momentum premium is significant and constant on the cross-section of shares listed on the JSE, even when adjusting for market risk, irrespective of weighting methodology applied. All of the risk-adjusted momentum premia are in excess of 1% per month and are statistically significant at the 1% level. The results of the GRS statistic tests further indicate that the momentum premium cannot be explained by market risk on the JSE. To further solidify the point, consider figure 5.1 below.

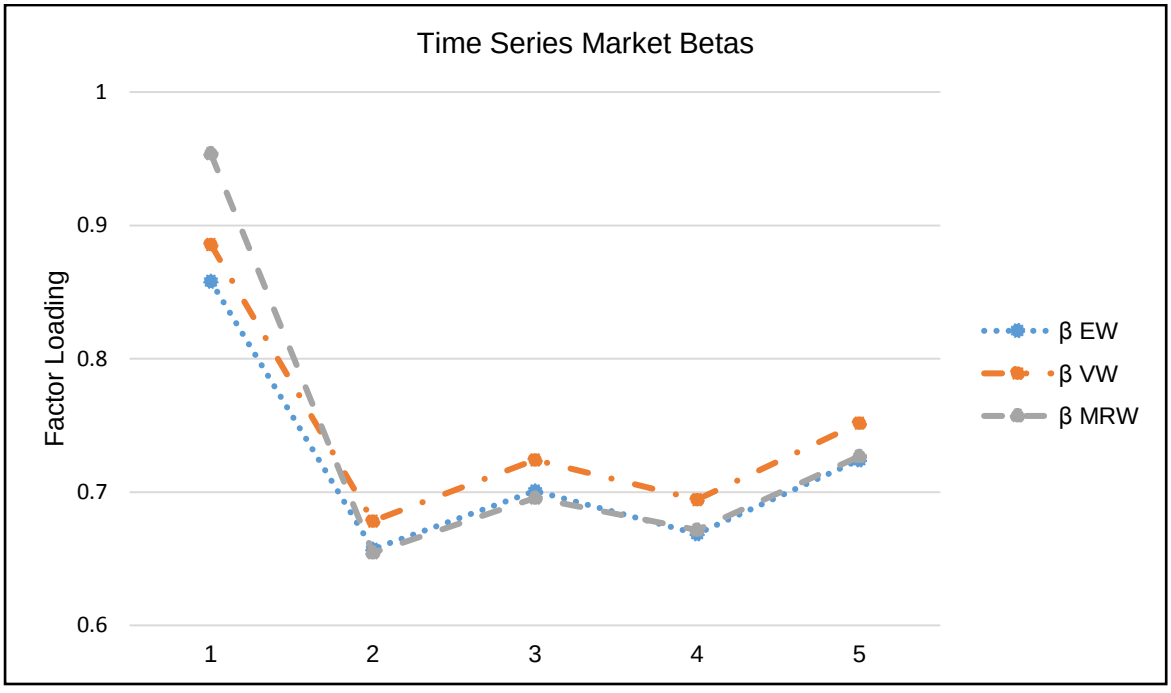


Figure 5.1: Time-series CAPM betas across momentum test portfolios

The figure displays the time-series betas for each of the test portfolios for the different weighting methodologies applied. The results indicate that the time-series betas are highly correlated, irrespective of weighting methodology. More importantly, the time-series betas consistently produce a W-shape as time-series betas are generally highest for the extreme winner portfolio, decrease at portfolios 2 to 4 and consistently increase for the extreme loser portfolio. The obvious expectation of the CAPM and efficient market hypothesis is that portfolio

returns follow the pattern of portfolio betas, however, as proven above, portfolio alphas decrease consistently and monotonically when moving from the extreme winner to the extreme loser quintile. The results of the market model time-series regressions therefore indicate that the momentum premium on the JSE cannot be explained by market risk and therefore, to some extent, adds to the plethora of evidence discrediting the CAPM on the JSE.

A corollary finding that is consistently present across the time-series regressions is that the momentum premium is largely attributable to the short position in the loser portfolio, consistent with the findings of Lesmond, Schill and Zhou (2004). The authors asserted that approximately 67% of the momentum premium is attributable to the short position in the extreme loser portfolio. By simply considering the absolute value contribution of the single portfolio time-series alphas of the extreme winner and extreme loser portfolios to the overall momentum premiums, the relative contribution of the long and short positions in the extreme winner and loser portfolios is expressed in the table that follows.

Position Contribution	Equally weighted	Value Weighted	Momentum Rank Weighted	Average
Long	35.58%	39.37%	38.89%	**37.95%**
Short	64.42%	60.63%	61.11%	**62.05%**

Table 5.4: Relative contribution to momentum premium risk-adjusted return using the CAPM specification

The results depicted above provide evidence consistent with the findings of Lesmond *et al.* (2004) as the short position in the extreme loser portfolio provides approximately 62% of the overall premium with the long position in the extreme winner portfolio providing around 38% on average. Drawing any definitive conclusion regarding the relative contribution of the long and the short position at this juncture would be premature. In order to determine an accurate contribution of the short and long position, a similar analysis will be conducted in the sections that follow using factor attribution models that consider other factor premia (risk-premia) that have been proven to explain share returns. The following section will test whether the momentum premium can be explained by a Fama and French (1995) three factor model using premia associated with size, value and market risk estimated using the cross-section of shares listed on the JSE.

5.4 TIME-SERIES TESTS OF MOMENTUM USING THE FAMA-FRENCH THREE FACTOR MODEL SPECIFICATION

The next factor pricing model to be applied in testing momentum is the highly popularized Fama-French three factor model, initially conceptualized by Fama and French (1992, 1995) and has received both global acclaim and infamy. The authors found that size, proxied by market capitalization and value, proxied by the book-to-market ratio, explained a large proportion of the variation in US share returns. In terms of the South African literature, van Rensburg and Robertson (2003), Auret and Sinclaire (2006), Basiewicz and Auret (2009), Gilbert, Strugnell and Kruger (2011) and more recently, Page and Auret (2013) found evidence in favor of both value and size premia being consistent and significant on the cross-section of shares listed on the JSE. It should be noted that a number of studies have recently found that the size premium has largely dissipated internationally and on the JSE. Auret and Cline (2010) considered calendar effects and the size premium on the JSE and found that a median split based on market capitalization generates no excess return. Page, Britten and Auret (2016) tested the limits to arbitrage hypothesis per Pontiff (1996) on the cross-section of shares listed on the JSE. The authors considered size, value and momentum and their relationship with transaction and liquidity constraints and idiosyncratic risk. A corollary finding that stemmed from the study was that the size premium is virtually non-existent on the JSE specifically when considering a time period that incorporates the most recent decade of share price data.

Fama and French (1996) tested the effectiveness of their three factor model against the medium term momentum premium of Jegadeesh and Titman (1993, 2001) and long-term reversal in share prices credited to Debondt and Thaler (1985, 1987). The authors found that the three factor model successfully explained the long-term reversal phenomenon, where extreme loser shares (measured over the previous 36-60 months) loaded positively on the value factor. However, when considering medium term momentum, the three factor model failed to explain the momentum premium, producing alphas that were higher than the CAPM specification applied. In the conclusion of the paper, the authors stated that the momentum anomaly is the biggest stumbling block to the efficient market hypothesis, as unlike size and value, momentum lacks a justifiable ‘risk’ based explanation.

Prior to conducting time-series attribution regressions on momentum using the Fama-French three factor model, size and value portfolios were constructed on a univariate basis. For the purpose of methodological consistency, identical price and liquidity filters were applied for the univariate sorts of size and value and portfolio rebalancing was conducted on a semi-annual basis where portfolio returns were calculated on a buy-and-hold basis. Therefore, at each

portfolio sort date, quintile portfolio breakpoints were applied to the cross-section of shares based on the book-to-market ratio and the natural logarithm of the previous month's market capitalization.

Simultaneously, shares were excluded if they had more than 100 cumulative zero daily trades over the previous trading year, a share price below 100 cents at portfolio initiation and achieved a turnover ratio in the bottom cross-sectionally estimated 15th percentile. Importantly, like all the ratios that incorporate accounting data within the Findata@wits database, in order to avoid look-ahead bias, accounting data is lagged six months, thereby assuming that accounting information is only fully disseminated to the public six months post the financial year end of the specific share in question. The univariate results of the size and value sorts are displayed in Tables 5.5 and 5.6 that follow.

	Big	2	3	4	Small	SMB
Average Return	0.9926%	0.9252%	0.8366%	0.6146%	0.6702%	-0.3223%
P-value	***0.0095******	***0.0096******	***0.0169****	***0.0699****	***0.0470****	***0.3129***
Standard Deviation	5.695%	5.310%	5.213%	5.062%	5.033%	4.780%
Market Beta	0.9704	0.7761	0.6871	0.6475	0.5029	-0.4676

Table 5.5: *Portfolio statistics for univariate quintile sorts on market capitalization. P-values are assigned asterisks based on statistical significance where *,**,*** indicate significance at the 10%, 5% and 1% level.*

	Value	2	3	4	Growth	VMG
Average Return	1.2365%	1.1926%	0.6833%	0.4136%	0.1103%	1.1262%
P-value	***0.0216****	***0.0115****	***0.0416****	***0.2211***	***0.7746***	***0.0201****
Standard Deviation	8.016%	7.019%	5.002%	5.055%	5.770%	7.214%
Market Beta	0.7998	0.7770	0.6732	0.6883	0.7651	0.0346

*Table 5.6: Portfolio statistics for univariate quintile sorts on the book-to-market ratio. P-values are assigned asterisks based on statistical significance where *,**,*** indicate significance at the 10%, 5% and 1% level.*

The results of the univariate sorts on size and value are largely consistent with both international and local literature. Considering the results of the size sorts, the results are consistent with those of Auret and Cline (2011) and more recently Page, Britten and Auret (2016), as there does not seem to be any significant size premium present on the cross-section of shares listed on the JSE. Considering the results of the extreme quintile portfolios,

the largest market capitalization portfolio achieves the highest return of 0.99% per month, just missing 12% per annum and is significant at the 1% level. The returns of the size sorted portfolios decreases up to portfolio 4 but experiences an increase in the smallest size quintile, achieving an average monthly return of 0.67% per month equating to 8.04% on an annualized basis and is significantly different from zero at the 5% level. Considering the zero cost size premium, the result implies that over the period January 1997 to September 2015, the size premium is actually negative as small capitalization shares underperform their large capitalization counterparts by 3.84% per annum on average. A possibility of the poor performance could be attributed to the relatively strict liquidity and transaction costs filters applied to the portfolio sorts, however, further exploration is beyond the scope of this chapter.

Conversely, the results of the value sorts are highly consistent with both international and local literature as the value premium seems to be consistent, positive and significant on the cross-section of shares listed on the JSE over the time period considered. The results add to evidence presented by van Rensburg and Robertson (2003), Auret and Sinclaire (2006), Basiewicz and Auret (2009), Basiewicz and Auret (2010), Gilbert, Strugnell and Kruger (2011), Page and Auret (2013) and Page, Britten and Auret (2016). The results indicate that as portfolios shift from value (high book-to-market shares) to growth (low book-to-market shares), portfolio returns decrease monotonically. Considering the results of the high book-to-market ratio portfolio, the portfolio achieved an average monthly return of 1.24% per month or 14.88% per annum and is significantly different from zero at the 5% level. It should be noted that the highest book-to-market ratio portfolio also achieved the highest monthly standard deviation at 8.02% per month. The low book-to-market or growth portfolio achieved an insignificant average monthly return of 0.11% per month or 1.32% per annum. The zero cost value minus growth strategy produces an average monthly return of 1.13% per month (13.56% per annum) and is significant at the 5% level.

In terms of methodological consistency, the size premium should in effect be excluded from the time-series regressions as the size premium cannot be considered a priced factor (or risk premium) as the results indicate that one is not compensated for holding size risk. This chapter (and this study as a whole) maintains a view that for the purposes of pragmatism and consistency with international literature, the size premium is to be included. Even though the size premium may not present a pure risk, it will provide insight into the sensitivity of momentum to the size effect and whether momentum loads on small or large capitalization shares. Prior to displaying and describing the results of the time-series regressions, it should be reiterated that the majority of literature that has used Fama-French factors in attempt to explain the momentum premium have failed. Defying logic, the majority of evidence indicates

that the momentum premium generally increases on a risk-adjusted basis, loads positively on smaller and medium capitalization shares and loads negatively on high value shares[13]. The results of the time-series regressions on momentum using the Fama-French three factor model are to be presented in the tables that follow. Once again, three sets of regressions are run where each set represents one of the weighting methodologies applied to the momentum quintile sorts, namely equal weighted, value weighted and momentum rank weighted portfolio returns.

	Momentum - Equal Weighting				
	α	β_{J203}	β_{SMB}	β_{VMG}	Adj. R^2
1	0.0066	1.1057	0.5619	-0.0955	74.07%
	0.0014***	***0.0000******	***0.0000******	***0.1015***	
2	0.0007	0.8291	0.4016	-0.1117	68.26%
	0.7027	***0.0000******	***0.0000******	***0.0153****	
3	-0.0025	0.8624	0.3483	0.0135	68.49%
	0.2135	***0.0000******	***0.0000******	***0.7833***	
4	-0.0036	0.8379	0.3763	-0.0323	61.62%
	0.0964*	***0.0000******	***0.0000******	***0.5297***	
5	-0.0087	0.8862	0.3630	-0.0433	62.62%
	0.0001***	***0.0000******	***0.0000******	***0.4155***	
1-5	0.0154	0.2195	0.1989	-0.0522	3.88%
	0.0000***	***0.0392****	***0.0491****	***0.6216***	
GRS	5.1846				
	0.0002***				

*Table 5.7 Time-series regression results conducted on equally weighted momentum test portfolios using the Fama-French model. P-values are assigned asterisks based on statistical significance where *,**,*** indicate significance at the 10%, 5% and 1% level.*

The results of the time-series regressions conducted on the equally weighted momentum quintile portfolios are largely consistent with international literature. Firstly, portfolio alphas decrease monotonically when moving from the extreme winner portfolio (Portfolio 1) to the extreme loser (Portfolio 5). The historical winner portfolio produces a time-series alpha of 0.66% per month, equivalent to 7.98% per annum and is significant at the 1% level. An investment in the extreme loser portfolio delivers a negative alpha of -0.87% per month, equivalent to a risk-adjusted loss of 10.5% per annum over the sample period. The zero-cost strategy that is long the extreme winner and short the extreme loser portfolio achieves an

[13] See Fama and French (1996) and more recently Asness *et al.* (2013)

excess return of 1.54%, equating to 18.4% per annum and is significant at the 1% level. As with the pure market model regressions presented above, the extreme winner portfolio achieves the highest market beta of 1.11, yet across the other portfolios, the variation in beta is minimal with portfolios 2-5 achieving market factor loadings in excess of 0.8.

The small minus big (SMB) factor loading is positive and significant at the 1% level across the equally weighted quintile portfolios, implying that momentum returns tend to maintain a higher correlation with medium and small stock returns as opposed to large capitalization shares. The highest size factor loading is achieved by the extreme winner portfolio, after which size factor loadings decrease monotonically, barring Portfolio 3. The result therefore implies that the extreme winner portfolio is positively related to the small size premium and is consistent with the findings presented in Chapter Four where small to medium capitalization shares displayed the highest momentum levels in independent and dependent bivariate sorts.

The results of the factor loadings on the value premium (VMG) are consistent with the findings of Fama and French (1996), Asness (1997), and Asness *et al.* (2013). The factor loadings of the extreme winner portfolios (Portfolios 1 and 2) load negatively on the value premium, both producing negative coefficients with the extreme winner portfolios VMG factor loading just missing significance at the 10% level. From portfolio 3 onwards, the factor loading is negative on average but statistically insignificant. The implication of the finding is that higher momentum portfolios tend to load negatively on value shares and load positively on glamour or growth shares.

The results presented are largely consistent with Asness (1997) as the author asserted that momentum shares are naturally glamour or growth shares while loser shares are normally value shares. Fama and French (1996) found that long-term reversal tends to load heavily on the value premium, while Asness *et al.* (2013) found that long-term reversal maintained an 80% correlation coefficient with the value premium across US shares. The results of the zero-cost momentum strategy indicate that both the excess returns on the JSE ALSI and the size premium are significant determinants of the momentum premium on the JSE as both factors are significant at the 5% level.

Conversely, the value premium maintains an insignificantly negative relationship with medium term momentum on the JSE, indicating the correct economic relationship described by Asness *et al.* (2013) but lacks statistical significance. The GRS test statistic indicates that the null is rejected at the 1%level of significance, demonstrating that the time-series alphas are not jointly equal to zero. The results imply that the Fama-French pricing model fails to explain the risk-

adjusted returns earned via an equal weighted momentum strategy implemented on the cross-section of shares listed on the JSE.

	Momentum - Value Weighting				
	α	β_{J203}	β_{SMB}	β_{VMG}	Adj. R^2
1	0.0074	1.1074	0.5048	-0.0918	74.11%
	0.0004***	***0.0000******	***0.0000******	***0.1165***	
2	0.0011	0.8257	0.3496	-0.1180	69.67%
	0.5452	***0.0000******	***0.0000******	***0.0107****	
3	-0.0019	0.8679	0.3115	0.0047	71.12%
	0.3262	***0.0000******	***0.0000******	***0.9236***	
4	-0.0032	0.8437	0.3324	-0.0315	61.63%
	0.1983	***0.0000******	***0.0000******	***0.6741***	
5	-0.0086	0.8883	0.3087	-0.0474	62.46%
	0.0009***	***0.0000******	***0.0000******	***0.4987***	
1-5	0.0160	0.2191	0.1961	-0.0445	3.43%
	0.0000***	***0.0448****	***0.0666****	***0.6929***	
GRS	5.0557				
	0.0002***				

*Table 5.8 Time-series regression results conducted on value weighted momentum test portfolios using the Fama-French model. P-values are assigned asterisks based on statistical significance where *,**,*** indicate significance at the 10%, 5% and 1% level.*

The results of the time-series regressions conducted on the market capitalization weighted momentum test portfolios are displayed in Table 5.8 and are fundamentally consistent with the equally weighted momentum sorts. As expected, Portfolio alphas decrease monotonically when moving from the extreme winner portfolio (Portfolio 1) to the extreme loser (Portfolio 5). The extreme winner portfolio produces a monthly alpha of 0.74% per month, equivalent to 8.9% per annum and is significant at the 1% level. Contrariwise, the extreme loser portfolio delivers a negative monthly alpha of -0.86% per month, equivalent to -10.4% per annum and is significant at the 1% level. The zero cost momentum strategy results in a time-series alpha of 1.6% per month, equivalent to 19.24% per annum and is significant at the 1% level. The results therefore indicate that the Fama-French model fails to explain the excess returns achieved by a market capitalization weighted momentum strategy applied on the JSE.

As with the equally weighted momentum sorts, the extreme winner portfolio achieves the highest loading on the market premium, yet the variation in market loadings is minimal, with all achieving market betas in excess of 0.82, indicating that market risk, although significant

cannot explain the variation in momentum returns. Akin to the results of the (univariate) market model regressions presented in section 5.3 above, the value weighted methodology produces marginally higher risk-adjusted returns than that of the equally weighted sorting procedure. The result is peculiar as value weighting will naturally up-weight towards larger market capitalization shares, yet the extreme winner portfolio loads highest on the SMB factor. A possible explanation could be directly related from the bivariate independent sort results presented in Chapter Four where the highest excess momentum return was produced by the medium market capitalization stratum. Similarly, an SMB factor loading of 0.5 can be interpreted as a loading closer to medium market capitalization shares possibly implying that the majority of share constituents in the extreme winner portfolio are more likely to be medium market capitalization shares. The rational however fails to explain why all of the momentum portfolios load positively (and significantly) on the SMB factor. Another potential explanation may be that a long only momentum strategy produces returns that to some extent mimic the principal component of small capitalization share returns, however, such an argument would be difficult to qualify without a significant size premium.

In terms of value, the results are virtually identical to those produced by the equally weighted momentum test portfolios. The top two momentum portfolios produce the largest negative VMG factor loadings, with the extreme winner portfolio just missing significance at the 10% level. The value loadings for portfolios 3-5 are all insignificant and negative, barring the value loading produced by portfolio 3. The results are therefore once again consistent with the findings of Fama and French (1996), Asness (1997) and Asness *et al.* (2013) with the highest momentum portfolios loading negatively on high value shares and therefore loading positively on glamour shares. Conversely, short/medium term momentum loser shares do not seem to load on value shares as the VMG factor loadings are insignificantly different from zero. A possible reason behind the result is alluded to by Asness *et al.* (2013) as the study found that loser shares only begin developing a positive correlation with value shares after a significant passage of time (between 36-60 months). The results of the GRS statistic further serve to confirm that the Fama-French three factor model fails to explain the risk adjusted returns earned by the market capitalization momentum strategy applied on the cross-section of shares listed on the JSE as the null is rejected at the 1% level, implying that time-series alphas are jointly significantly different from zero.

The final set of regression results are presented in Table 5.9 and relate to regressions run on the momentum rank weighted momentum portfolio returns. Parallel to the findings presented in section 5.3, the momentum rank weighting produces the largest time-series alphas. The extreme winner portfolio produces a risk-adjusted return of 0.86% per month, equivalent to

10.31% per annum and is significant at the 10% level. Comparing the annualized returns of the momentum rank weighted winner portfolio to that of the equal and value weighted winners, the momentum rank weighting results in 2.33% and 1.44% more risk-adjusted profit per annum on average, but falls short in terms of comparative statistical significance as both the equal and value weighted winner alphas are significant at the 1% level. The extreme loser portfolio produces a negative alpha of 0.91% per month, equivalent to -10.93% per annum and is significant at the 1% level. The zero cost momentum strategy produces a time-series alpha of 1.77% per month, equating to 21.24% per annum and is significant at the 1% level, equating to 2.81% and 2% more than the equal and valued weighted zero cost strategies on an annual basis, respectively. Notably, the momentum rank weighted extreme winner portfolio produces the highest market beta of 1.29, while portfolios 2-5 produce market betas in excess of 0.82. Considering the portfolio loadings on the SMB factor, consistent with the equal and value weighting methodologies, all of the momentum portfolios produce positive and significant coefficients. As mentioned, a plausible reason could be related to momentum returns being highly correlated with returns achieved by small and medium capitalization shares, however, the lack of an identifiable size effect casts doubt on the relationship between momentum and size.

Jegadeesh and Titman (2001) found a similar phenomenon, where both the winner and loser portfolios produced positive significant loadings on the SMB factor. The authors asserted that such an outcome is plausible since smaller volatile shares will generally be found in the two extreme portfolios. In terms of the findings presented in Table 5.9 below, the reasoning seems incomplete as all of the momentum portfolios load positively on the SMB factor.

The results of the factor loadings on VMG are the most consistent with international literature, specifically Fama and French (1996), Asness (1997), Jegadeesh and Titman (2001) and more recently, Asness *et al.* (2013). Portfolios 1 and 2 achieve significantly negative value factor loadings, with the extreme winner portfolio achieving the most (economically) negative factor loading (-0.191) and is significant at the 10% level. The result complies with the assertion that extreme winner shares are highly correlated with growth or glamour shares and are therefore negatively correlated with value or distressed shares. Consistent with the equal and value weighted time-series regressions, portfolios 3-5 produce insignificant factor loadings on value. As mentioned, Asness (1997) found that loser shares should typically achieve higher value loadings, as these are shares that have experienced relative distress. The fact that the lower momentum portfolios do not produce significant positive factor loadings may be attributable to the six month holding period applied in the momentum quintile sorts. Considering long-term reversal and value, a historically poor six month performance cannot be used to classify a

share as distressed in terms of value or a long-term loser, thereby explaining the insignificant value/distress loadings achieved by portfolios 3-5.

	Momentum - Momentum Rank Weighting				
	α	β_{J203}	β_{SMB}	β_{VMG}	Adj. R^2
1	0.0086	1.2893	0.7768	-0.1912	44.85%
	0.0579*	***0.0000****	***0.0000****	***0.0894****	
2	0.0004	0.8272	0.4019	-0.1056	67.25%
	0.8214	***0.0000****	***0.0000****	***0.0107****	
3	-0.0025	0.8565	0.3485	0.0065	67.93%
	0.2092	***0.0000****	***0.0000****	***0.8965***	
4	-0.0037	0.8426	0.3791	-0.0283	61.32%
	0.1455	***0.0000****	***0.0000****	***0.7018***	
5	-0.0091	0.8896	0.3645	-0.0410	62.32%
	0.0004*	***0.0000****	***0.0000****	***0.5403***	
1-5	0.0177	0.3997	0.4123	-0.1503	5.57%
	0.0028*	***0.0065****	***0.0053****	***0.3264***	
GRS	4.3311				
	0.0009*				

*Table 5.9: Time-series regression results conducted on momentum rank weighted momentum test portfolios using the Fama-French model. P-values are assigned asterisks based on statistical significance where *,**,*** indicate significance at the 10%, 5% and 1% level.*

The results of the time-series regressions carried out on the momentum rank weighted quintile produce a unique finding, specifically related to zero-cost momentum strategy presented in the second last row of Table 5.9. Unlike the equal and value weighted zero cost strategies, the factor loadings of the explanatory variables are economically higher and statistically more significant. Considering the market risk premium, the factor loading is 0.4 and significant at the 1% level. Similarly, the SMB factor loading is 0.41 and is significant at the 1% level. Lastly, the VMG factor loading achieves the most negative factor loading of -0.15, but is statistically insignificant. The biggest peculiarity is the time series alpha, which in the face of the highest statistical factor loadings of the three weighting methodologies, achieves by far the highest risk-adjusted excess return. Leading from this, the GRS test statistic rejects the null hypothesis of joint equality across portfolio alphas. The results therefore palpably indicate that the Fama-French three factor model fails to explain the cross-sectional variation in momentum returns.

Lastly, the overall results of the application of a Fama-French three factor model are consistent with international literature. Irrespective of weighting methodology applied, the Fama-French three factor alphas are consistently greater than the alphas generated when using the CAPM specification. The finding is best described via figures 5.2-5.4 below.

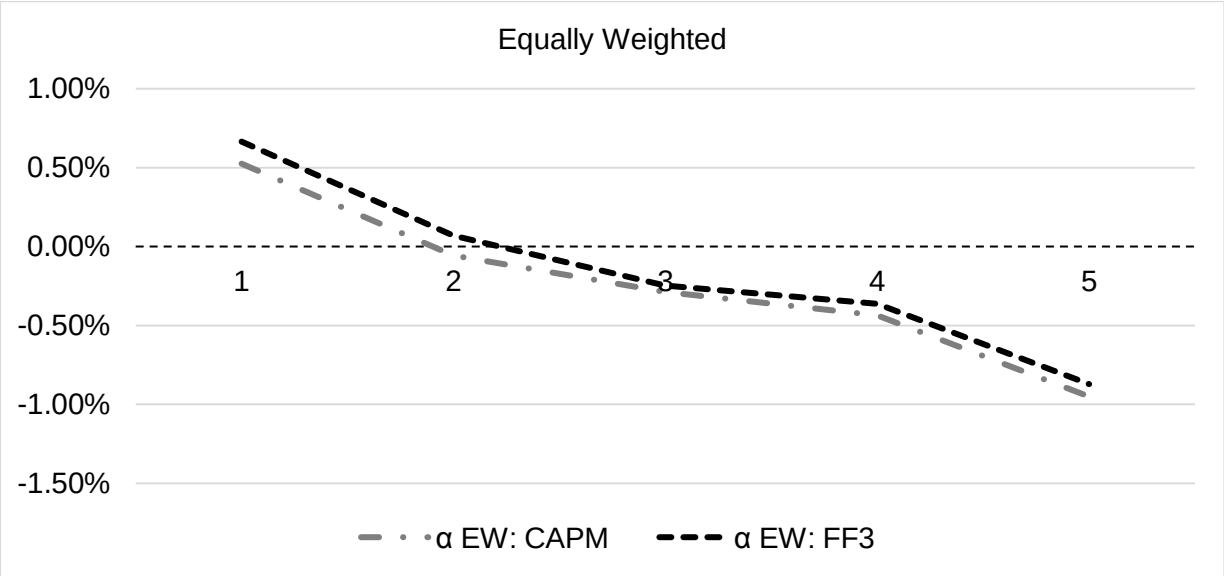


Figure 5.2: Comparison of equally weighted momentum alphas generated via the CAPM and Fama-French time-series regressions

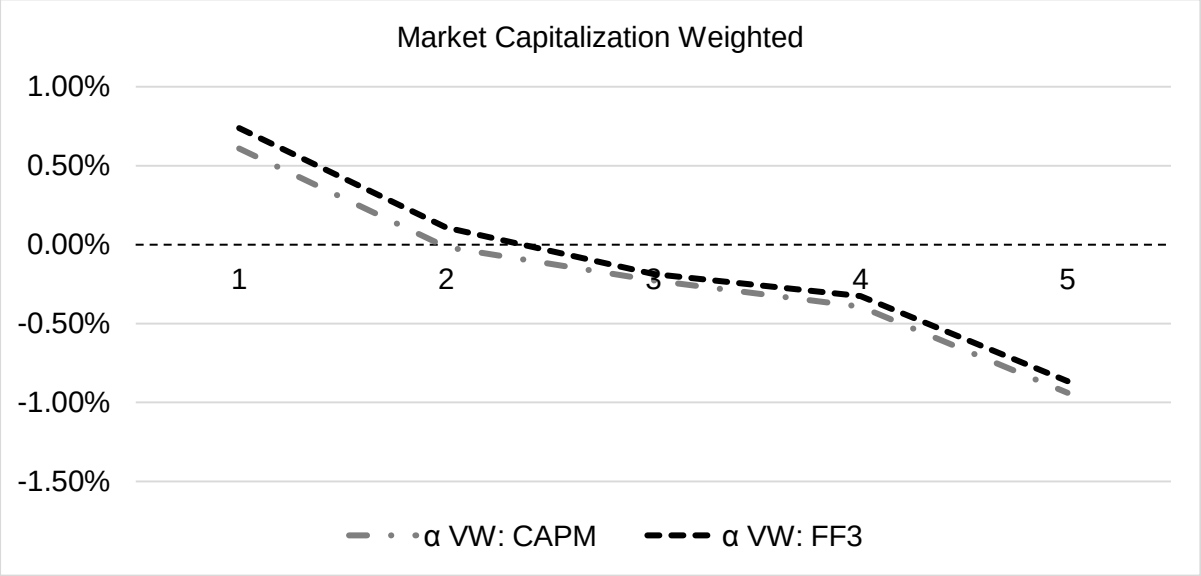


Figure 5.3: Comparison of value weighted momentum alphas generated via the CAPM and Fama-French time-series regressions

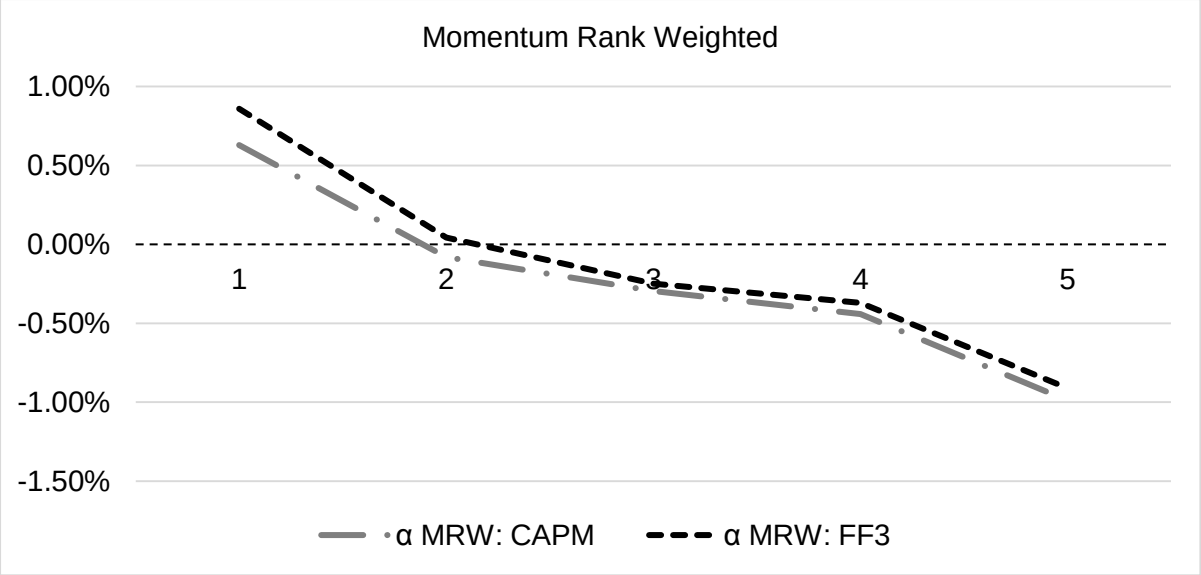


Figure 5.4: Comparison of momentum rank weighted momentum alphas generated via the CAPM and Fama-French time-series regressions

The figures all present virtually identical information as each figure indicates that Fama-French time-series alphas are consistently greater than those produced by the pure CAPM specification. More importantly, the key difference is mainly seen in the extreme winner portfolios, where the time-series alphas of portfolios 1 and 2 consistently plot above the time-series alphas estimated via the CAPM specification, irrespective of which weighting methodology is applied. Conversely, the time-series alphas of the lower momentum "loser" portfolios are virtually identical for both specifications, with the gap narrowing consistently from Portfolio 3 onwards. The results add a further dimension to the findings, specifically when related to the CAPM specification time-series alphas. Table 5.4 above presented proof in favor of the noted hypothesis that the majority of the excess return (momentum premium) stems from the short position in the extreme loser portfolio as the winner time-series alphas only provide 38% of the total premium on average. Conducting an identical test on the time-series alphas estimated using the Fama-French specification indicates that the long-position in winner shares produces a larger proportion of the risk-adjusted momentum premium. The results are presented in Table 5.10 that follows.

Position Contribution	Equally Weighted	Value Weighted	Momentum Weighted	Average
Long	43.26%	46.07%	48.53%	45.95%
Short	56.74%	53.93%	51.47%	54.05%

Table 5.10: Relative contribution to momentum premium risk-adjusted return using the Fama-French specification

The results of the relative contributions presented above indicate that when using the Fama-French specification, the contribution of the long position in winner shares provides approximately 46% of the total risk-adjusted momentum premium. Additionally, when comparing the Fama-French and CAPM attribution results in terms of the average contributions to the overall portfolio alpha, the average difference in contribution of the winner portfolio to the total risk-adjusted premium is 8.01% more and is significant at the 5% level. The result implies that merely applying a Fama-French regression increases the contribution of the long-position in the winner portfolio to the overall momentum premium.

When comparing the weighting methodologies, consistent with the CAPM specification, the greatest long winner contribution is achieved by the momentum rank weighted winners (48.5% achieved using the Fama-French specification and 38.9% via the CAPM) and the lowest is that of the equal weighted methodology (43.3% and 35.6% achieved by the Fama-French and CAPM specifications respectively). In summary, the results of the Fama-French estimated time-series alphas indicate, like those of the CAPM, the momentum premium is significant, positive and present on the cross-section of shares listed on the JSE. Consistent with the findings of Jegadeesh and Titman (2001), the time-series alphas generated using a Fama-French model seem to exacerbate the risk-adjusted returns achieved via a momentum strategy. Importantly, even with factors loadings being significant and economically large in most cases (barring VMG in the lower momentum portfolios), the Fama-French factors fail to explain excess returns, therefore indicating that the momentum premium is not driven by the size or value premium.

5.5 TIME-SERIES TESTS OF MOMENTUM USING BETA, IDIOSYNCRATIC RISK, CURRENCY RISK AND LIQUIDITY FACTOR PREMIUMS (FIVE-FACTOR MODEL)

The results of the Fama-French three factor model time-series regressions are consistent with international findings as neither size nor value are able to explain the momentum phenomenon on the JSE. More recently, there has been a growing interest in other factor mispricing's that have been found to drive share returns, negating the EMH and CAPM. Moving away from the Fama-French factors, a number of the 'new' factor premia fit neatly within the ever-growing 'behavioral' framework in determining the cross-sectional variation in returns, specifically the low beta and low volatility anomalies. Additionally, there are other less considered factors that have not been conventionally applied to describing the momentum premium or share returns, namely liquidity and currency risk. The "new" factors or premia lead to the natural development of an attribution model that can be used (in attempt) to explain momentum returns, hence the

impetus to combine the low beta effect, low idiosyncratic risk, currency risk and liquidity into a single explanatory model.

The rationale is both simple and logical as both low volatility and low beta are relatively new findings and seem to be consistent across markets and time. Liquidity has been considered in tandem with momentum on numerous occasions, where studies have found both inverse and positive relationships between momentum and the (il)liquidity premium. Currency risk is highly topical, specifically across emerging markets, with changes in exchange rates being used as a proxy for macro-economic risk. Both liquidity and currency risk have yet to be consistently considered as priced factors that explain share returns, hence are included in the attribution regressions to be conducted in this section. If the considered factors are present and produce positive consistent premiums, the momentum effect on the cross-section of shares listed on the JSE may be a manifestation of one or a combination of the "new" or "unexplored' factor premia. The section that follows will explore, in a multivariate setting, whether the low beta, low volatility, currency risk or liquidity premium explain the momentum premium on the JSE, to the extent that momentum risk-adjusted excess returns are not significantly different from zero. Prior to describing the univariate sorting methodology and results of the factor premia to be used as independent attribution variables, a brief summary of the salient evidence surrounding the explanatory variables and their relationship with momentum is deemed necessary. The oldest and most explored factor premia in conjunction with momentum to be considered is liquidity. Lee and Swaminathan (2000) found a positive relationship between momentum and liquidity, proxied by trading volume. The authors found that momentum seemed to maintain an inverse relationship with illiquidity in that highly liquid winners outperformed highly liquid losers by a greater margin than their less liquid counterparts.

Sadka (2006) considered the effects of liquidity on momentum using the Glosten and Harris (1998) method of determining the fixed and variable components of share liquidity. In cross-sectional regressions, the author found that the variable component of liquidity explains approximately 60% of the momentum premium achieved on the cross-section of shares listed on the NYSE over period January 1983 to August 2001. Hameed and Kusnadi (2002) found that momentum maintains a positive and significant relationship with liquidity, proxied by turnover, across shares listed in various markets across the Asia Pacific basin. In examining the feasibility of a four factor Carhart (1997) model on the cross-section of shares listed on the Canadian stock exchange, L'Her, Masmoudi and Suret (2004) found that liquidity maintained an insignificant relationship with momentum profits. More recently, Page, Britten and Auret (2013) found a positive and significant relationship between momentum and liquidity, proxied

by turnover, on the cross-section of shares listed on the JSE over the period January 1995 to December 2010.

Baker, Bradley and Wurgler (2011) and Frazzini and Pedersen (2014) both found evidence in favor of the low beta phenomenon where both studies linked the low beta phenomenon to the 'irrational" investor behavior and the "limits to arbitrage" hypothesis, where the former is a "behavioral" based explanation while the latter is rational and "risk" based. Without much effort, both behavioral models and limits to arbitrage explanations have been utilized in attempt to explain the momentum premium, therefore, if the low beta phenomenon shares commonality in terms of hypothetical reasoning, such commonality provides impetus for incorporation of the low beta premium within a multivariate test setting.

The low volatility effect was also explored by Baker, Bradley and Wurgler (2011), however, the connection to momentum is largely inspired by the 'limits to arbitrage' argument of Pontiff (1996). McLean (2010) and more recently, Page, Britten and Auret (2016) found that unlike value and long-term reversal, momentum returns do not seem sensitive to variations in volatility. Both results imply that the 'limits to arbitrage' hypothesis fails to explain momentum, in that the non-presence of a positive relationship implies that smart money is not prevented from engaging in momentum arbitrage as they are not detracted by the "holding costs" associated with the short position in loser shares. Lastly, following the work of Barr and Kantor (2005), Page, Britten and Auret (2015) considered whether currency risk can be applied in a stylistic factor framework on the JSE. The authors found that over the period January 1996 to December 2013, rand tracker shares or shares with significantly negative dollar/Rand betas significantly outperformed rand hedge shares (significantly positive dollar/Rand betas). Further, the authors found that the underperformance of rand hedge shares was consistent with a risk-based explanation as rand hedge shares were found to hedge against significant depreciations in the dollar/Rand exchange rate.

For the purpose of conducting the time-series regressions, excess factor premium time-series returns are estimated based on liquidity adjusted beta, idiosyncratic risk, liquidity proxied by turnover and rand beta under identical price and liquidity restrictions as the quintile momentum test portfolios. Like the univariate momentum sorts, portfolio rebalancing is conducted on a semi-annual basis where portfolio returns are calculated on a buy-and-hold basis. At each portfolio sort date, quintile portfolio breakpoints are applied to the cross-section of shares based on the liquidity adjusted beta, idiosyncratic risk and rand beta measured over the previous 36 to 60 months and average turnover measured over the previous 12 months. Simultaneously, shares are excluded if they have more than 100 cumulative zero daily trades over the previous trading year, a share price below 100 cents at portfolio initiation and achieve

a turnover ratio in the bottom cross-sectionally estimated 15th percentile. Notably, since the liquidity adjusted beta, rand beta and idiosyncratic risk measures utilize OLS regression estimations, shares are excluded at each portfolio sort if they have less than 36 months of historical returns (the same rule is obviously not applied to univariate turnover sorts). The results of the beta, rand beta, idiosyncratic risk and turnover sorted portfolios are presented in the tables that follow.

	High Idio	2	3	4	Low Idio	LVMHV
Average	-0.4820%	0.4200%	0.6000%	0.9300%	1.0880%	1.5710%
P-value	***0.2590***	***0.3233***	***0.1070***	***0.0432****	***0.0018*****	***0.0000*****
Standard Dev.	6.381%	6.040%	5.542%	6.824%	5.187%	5.212%
Market Beta	0.8432	0.7416	0.7537	0.7521	0.7218	-0.1133

*Table 5.11: Portfolio statistics for univariate quintile sorts on idiosyncratic risk. P-values are assigned asterisks based on statistical significance where *,**,*** indicate significance at the 10%, 5% and 1% level.*

	High Beta	2	3	4	Low Beta	LBMHB
Average	-0.1920%	0.5130%	0.8220%	0.7160%	1.3130%	1.4940%
P-value	**0.6750**	**0.1560**	**0.0253****	**0.2220**	**0.0123****	**0.0091*****
Standard Dev.	6.703%	5.328%	5.438%	8.568%	7.736%	8.542%
Market Beta	0.8742	0.7163	0.7632	0.8943	0.6420	-0.2731

*Table 5.12: Portfolio statistics for univariate quintile sorts on liquidity adjusted beta. P-values are assigned asterisks based on statistical significance where *,**,*** indicate significance at the 10%, 5% and 1% level.*

	Rand Hedge	2	3	4	Rand Tracker	RHMRT
Average	0.6093%	0.8365%	0.9791%	0.9466%	0.9407%	0.3314%
P-Value	***0.0975****	***0.0111****	***0.0035*****	***0.0052*****	***0.0129****	***0.2965***
Standard Dev.	5.479%	4.889%	4.964%	5.024%	5.620%	4.740%
Beta	0.7642	0.6590	0.6820	0.6604	0.7564	-0.0079

*Table 5.13: Portfolio statistics for univariate quintile sorts on rand beta. P-values are assigned asterisks based on statistical significance where *,**,*** indicate significance at the 10%, 5% and 1% level.*

	High Liquidity	2	3	4	Low Liquidity	HLMLL
Average	0.8770%	0.9581%	0.8955%	0.7923%	0.5230%	0.3540%
P-value	***0.0280****	***0.0052*****	***0.0082*****	***0.0127****	***0.1080***	***0.2270***
Standard Dev.	5.947%	5.092%	5.033%	4.732%	4.861%	4.383%
Beta	0.9226	0.7644	0.7504	0.6413	0.5790	0.3436

*Table 5.14: Portfolio statistics for univariate quintile sorts on average turnover. P-values are assigned asterisks based on statistical significance where *,**,*** indicate significance at the 10%, 5% and 1% level.*

The results of the quintile sorts on idiosyncratic risk, beta, rand beta and liquidity are presented in Tables 5.11, 5.12, 5.13 and 5.14 above. Initially considering the idiosyncratic risk sorts, consistent with the findings of Malkiel and Xu (2006), Ang, Hodrick, Xing and Zhang (2009) and Baker, Bradley and Wurgler (2011), the low volatility (idiosyncratic risk) phenomenon seems to be present and consistent on the cross-section of shares listed on the JSE. Table 5.11 indicates that the highest idiosyncratic risk portfolio achieves the lowest average return of -0.482% per month, equivalent to a loss of 5.8% per annum on average. The highest monthly average return is achieved by the low idiosyncratic risk portfolio, achieving an average monthly return of 1.09%, equating to an annualized return of 13.06% and is significant at the 1% level. The results further indicate the consistency of the low volatility premium as portfolio returns increase monotonically when moving from the highest idiosyncratic risk portfolio to the lowest, resulting in a zero cost low volatility premium of 1.57% per month, equating to 18.8% per annum that is significantly different from zero at the 1% level. The final rows of the table depict the *ex-post* estimated market betas and univariate standard deviations of the idiosyncratic risk sorted portfolios. As expected, the ex-post portfolio standard deviations decrease when moving from the highest idiosyncratic risk portfolio, achieving a monthly standard deviation of 6.381% compared to 5.19% achieved by the lowest idiosyncratic risk portfolio, indicating that idiosyncratic risk across shares (portfolios) is relatively consistent through time.

Interestingly, the same effect seems to apply to portfolio betas, as portfolio betas tend to decrease when moving from the highest to lowest idiosyncratic risk portfolios. The result of the ex-post betas of the idiosyncratic risk quintile portfolio potentially indicate that the low volatility premium may be driven by the low-beta premium, as the low volatility portfolio consistently maintains a low market beta, however, since the methodology applied in estimating idiosyncratic risk entails orthogonalising returns on the J203 ALSI, the likelihood of the low beta premium driving the low volatility premium is minimal.

Table 5.12 portrays the results of the portfolio sorts conducted on market beta where time-series betas are adjusted for thin trading using the approach of McClelland, Wright and Auret (2015). The results of the portfolio sorts are highly consistent with the findings Black (1972), van Rensburg and Robertson (2003), Baker, Bradley and Wurgler (2011) and most recently, Frazinni and Pedersen (2014). The first row indicates that on a gross-average return basis, portfolio returns increase monotonically when moving from high beta shares to low beta

shares. The highest beta quintile achieves a statistically insignificant negative average monthly return of -0.19% per month or -2.3% per annum. Conversely, the extreme low beta quintile achieves an average monthly return of 1.3% per month, equivalent to 15.6% per annum and just misses significance at the 1% level. The final column of the table presents the fictional zero cost investment strategy of investing long in the low beta quintile and shorting the high beta quintile, equivalent to the "Betting against Beta" or "BAB" portfolio described by Frazinni and Pedersen (2014).

The low minus high beta portfolio (LBMHB) achieves an excess return of 1.49% per month, equivalent to an average annual return of 17.9% and is significantly different from zero at the 1% level. Unlike the idiosyncratic risk sorts, the average returns of the beta quintile portfolios do not produce a perfect monotonic relationship with beta, as portfolio 3 produces higher returns than both quintiles 2 and 4. The result therefore indicates that the low beta anomaly may not be as consistent as that of the low volatility phenomenon across shares on the JSE, but it is certainly as persistent, achieving an excess factor return of over 1% per month. Considering the market beta of each of the quintile portfolios, the extreme portfolios produce betas consistent with their ex-ante sorting criteria, where the high beta portfolio achieves a time-series beta of 0.87 while the low beta portfolio produces a time-series beta of 0.6. The variation in ex-post sorting betas is anything but systematic or monotonic as the time-series beta decreases for quintile 2, increases for quintiles 3 and 4 and decreases for quintile 5. Therefore, like the average returns of the beta sorted portfolios, ex-post portfolio betas are not as consistent as ex-post portfolio standard deviations achieved by the idiosyncratic risk sort presented in Table 5.11.

Similarly, unlike the idiosyncratic risk sorts, the ex-post portfolio standard deviations do not translate into any form of pattern, as the high beta quintile produces a standard deviation of 6.7% per month, while the low beta portfolio produces the second highest ex-post portfolio standard deviation of 7.74% per months. The result of the ex-post standard deviations indicate a positive finding in favor of the low beta premium as the excess returns of low beta shares over their high beta counterparts is definitely not driven by the low volatility phenomenon.

The currency beta portfolio results are somewhat consistent with the findings of Page, Britten and Auret (2015). The rand hedge portfolio (Portfolio 1) achieves the lowest return of 0.61% per month, equating to 7.31% per annum and is just significant at the 10% level. The rand tracker portfolio achieves a return of 0.941% per month, equating to 11.3% per annum and is significant at the 5% level. The zero cost currency risk portfolio, which represents a fictitious long and short position in the rand tracker and rand hedge portfolios achieves a positive excess return of 0.33% per month, equivalent to 3.97% per annum but lacks statistical

significance. The results therefore display a significantly weaker premium than that described by Page, Britten and Auret (2015). Additionally, the relationship between portfolio returns and currency risk is not linear or monotonic as gross returns increase over portfolios 1 and 2, reach a pinnacle at portfolio 3 and decrease thereafter.

The results are however consistent with Page, Britten and Auret (2015) in terms of ex-post risk proxies. The results indicate that currency beta sorted portfolios fail to produce discernibly different ex-post beta or idiosyncratic risk estimates. The rand hedge and rand tracker portfolios produce virtually identical market betas of 0.76 while the rand tracker portfolio produces a marginally higher standard deviation of 5.62% compared to 5.48% achieved by the rand hedge portfolio. A potential cause of the difference in results when compared to Page, Britten and Auret (2015) may be largely due to methodological variances. The authors applied 33rd / 66th tercile portfolio sorts as opposed to quintiles while the assumed portfolio holding period was 12 months compared to six months applied in the tests presented above. A possible cause of the weaker results could be that the currency risk only manifests in the second six months of an annual holding period and that the effect is highly sensitive to the portfolio breakpoints applied for sorting. Investigation into the optimal methodology to apply when investigating currency risk on the JSE is an avenue of further research and beyond the scope of this study. The key outcome is the factor premium based on currency exposure that may explain a portion of the momentum premium on the cross-section of shares listed on the JSE.

The final univariate factor sort to be discussed is the quintile sorts conducted on liquidity proxied by share turnover, expressed in Table 5.14. As mentioned, shares are sorted into quintiles based on their historical average turnover, where turnover is calculated as volume scaled by number of shares in issue. The benefit of turnover, as expressed by Ibbotson, Chen, Kim and Hu (2013), is that unlike pure volume, turnover is not biased by size of the underlying share. The results of the univariate quintile sorts are largely inconsistent with those presented by Amihud and Mendelson (1986) and more recently Ibbotson, Chen, Kim and Hu (2013). The quintile portfolio returns seem to maintain an inverse relationship with liquidity when proxied by turnover. The highest liquidity portfolio achieves a monthly average return of 0.88% per month, equivalent to 10.5% per annum and is significant at the 5% level. The lowest liquidity quintile portfolio produces an average monthly return 0.52% per month, equivalent to 6.3% per annum and just misses significance at the 10% level. The results therefore indicate that on the cross-section of shares listed on the JSE, low liquidity shares do not outperform their high liquidity counterparts when using turnover as a proxy for liquidity.

Conversely, the relationship between returns and liquidity seems to be inverted when compared to international studies, as high liquidity shares outperform low liquidity shares on the JSE. Considering the last column which presents the zero cost strategy of investing in high liquidity shares and simultaneously shorting low liquidity shares, the excess liquidity premium achieved is an insignificant 0.35% per month, equating to 4.2% per annum. Considering the variation in liquidity quintiles based on ex-post market beta and idiosyncratic risk, market betas decline monotonically when moving across the liquidity quintiles. The highest liquidity quintile produces the highest market beta of 0.92 while the lowest liquidity quintile produces the lowest market beta of 0.58. The result is logical as the market proxy, the J203 ALSI, is a value weighted market portfolio that naturally maintains a higher weighting in more liquid, larger shares. Similarly, the highest liquidity portfolios produce the highest idiosyncratic risk values, however the variation in ex-post portfolio standard deviations is not as extreme as that seen in the ex-post market betas.

The results of the univariate liquidity sorts result in two divergent possible explanations. Firstly, it is possible that turnover is not an adequate proxy for the liquidity on the cross-section of shares listed on the JSE, hence the presence of an inverse liquidity premium may be attributable an error-in-variable, implying a Type 1 statistical error. A second, and possibly more plausible explanation, can be directly related to the size premium on the JSE. As described above, the size premium on the JSE has largely dissipated over the most recent decade. The liquidity premium can be logically linked to the size premium, as small capitalization shares are generally less liquid than their large market capitalization counterparts. If the size premium is directly linked and even explained by the liquidity premium, then its non-presence may be as a result of liquidity premium being non-existent on the JSE. Lastly, the non-presence of the liquidity premium may be linked to the univariate sort procedures used in estimating the liquidity portfolios.

As mentioned, all sorts require a minimum price of 100 cents, cumulative zero daily trades over the previous 12 months less than 100 and achieve a turnover in excess of the cross-sectionally estimated 15th percentile. The result is that the underlying universe of investable shares is synthetically (and by design) more liquid, limiting the possibility of finding a liquidity premium as there is no access to truly illiquid shares. However, as described previously, it may be premature to exclude liquidity and currency risk from the time-series analysis, as even though there are no explicit premiums, both factors may provide insight into risk dynamics of the momentum premium on the JSE.

The results of the time-series attribution regressions using the augmented five factor model comprising of factor premia represented by excess returns earned by low beta over high beta

shares, low volatility shares over high volatility shares, high currency risk over low currency risk shares and high liquidity minus low liquidity shares are presented in the tables that follow. As previously described, three variations of momentum are tested, assuming equal, value and momentum rank weighting. A further regression is conducted on the zero cost long short momentum strategy in order to define the risk-adjusted momentum premium under the considered factors.

	Momentum - Equal Weighting						
	α	β_{J203}	β_{BAB}	β_{LowVol}	β_{LIQ}	β_{ZAR}	Adj. R^2
1	0.0083	0.8773	0.0413	-0.2894	-0.0914	0.0582	65.07%
	0.0036*	***0.0000****	***0.4133***	***0.0001****	***0.2223***	***0.3980***	
2	0.0000	0.7016	0.0529	-0.1116	-0.0990	0.1833	58.46%
	0.9836	***0.0000****	***0.3671***	***0.1371***	***0.0350****	***0.0002****	
3	-0.0035	0.7861	0.0973	-0.0226	-0.1479	0.1427	64.52%
	0.1330	***0.0000****	***0.0226****	***0.6066***	***0.0166****	***0.0182****	
4	-0.0043	0.6715	0.0397	-0.0926	0.0157	0.2138	56.43%
	0.0978*	***0.0000*****	***0.4798***	***0.0750****	***0.8511***	***0.0039****	
5	-0.0079	0.7197	-0.0181	-0.1547	-0.0460	0.1137	57.33%
	0.0016*	***0.0000****	***0.6828***	***0.0048****	***0.4475***	***0.0307****	
1-5	0.0162	0.1576	0.0594	-0.1347	-0.0455	-0.0555	2.82%
	0.0000*	***0.1022***	***0.3152***	***0.1627***	***0.7087***	***0.5492***	
GRS	5.9199						
	0.0001*						

*Table 5.15 Time-series regression results conducted on equal weighted momentum test portfolios using the augmented attribution model that considers low beta, low volatility, currency risk and liquidity. P-values are assigned asterisks based on statistical significance where *,**,*** indicate significance at the 10%, 5% and 1% level.*

Table 5.15 displays the results of the attribution regressions where time series alphas appear in the second column, factor loadings in columns three to seven and adjusted R^2 for each regression in the final column. The final two rows depict the GRS test statistic and probability value assuming a right-tailed F-distribution. Focusing on the time-series alphas, once again, the intercepts of the time-series regressions indicate a significant momentum premium on the cross-section of shares listed on the JSE. The extreme winner momentum quintile (Portfolio 1) produces a risk-adjusted excess return of 0.83% per month, equivalent to 10.01% per annum and is significant at the 1% level. Again, momentum intercepts decrease consistently and monotonically when moving towards the extreme loser portfolio, with Portfolio 5 producing the lowest time-series alpha of -0.79%, equating to a negative average annual return of -9.45%

and is significantly different from zero at the 1% level. The zero cost equally weighted momentum portfolio produces a time-series alpha of 1.62% per month, equating to 19.45% per annum and is significant at the 1% level. The results therefore indicate that the equally weighted momentum premium on the JSE cannot be explained by the low beta, low volatility, currency risk or the liquidity premium, as momentum is consistent, present and positive *ex-post* factor adjustment.

Considering the factor loadings, as with the previous tests, the momentum portfolios all produce significant and positive market factor loadings, ranging from 0.877 for the extreme winner portfolio to 0.672 achieved by portfolio 4. The factor loadings achieved on the low beta premium are positive for Portfolios 1-4 but only significant for Portfolio 3. The results seem to indicate that the highest momentum portfolio does load positively on low beta shares while the loser portfolio loads more on high beta shares, however the lack of significance implies that the performance of both portfolios is not driven by the low beta premium.

The factor loadings on the low volatility premium are more promising. Both the equal weighted extreme winner and loser portfolios load negatively on the low volatility premium, with both factor loadings being significant at the 1% level. The results indicate that both the extreme portfolios are made up of higher idiosyncratic risk shares thereby intimating that variations in underlying volatility fail to drive the momentum premium on the JSE. The results are therefore highly consistent with the findings of Page, Britten and Auret (2016), as volatility fails to drive momentum on the cross-section of shares listed on the JSE.

The results of the liquidity factor fail to depict any clear relationship with momentum. Firstly, per Page, Britten and Auret (2013), one would expect a positive factor loading in the higher (winner) momentum portfolios and a negative factor loading in the lower (loser) momentum portfolios. Conversely, the extreme winner portfolio produces an insignificantly negative factor loading of -0.091 as does the extreme loser portfolio, achieving a factor loading of -0.037. The results therefore imply that even though the winner portfolio loads more on low liquidity returns, the liquidity premium does not seem to drive returns on the JSE. Lastly, the factor loadings on the rand tracker premium indicate that extreme winner portfolio seems largely unaffected by currency risk, however Portfolios 2 to 5 all load positively and significantly on the rand tracker premium, implying that loser or relative poorer performing shares tend to be more sensitive to exchange rate risk.

The final row depicts the zero cost momentum portfolio or excess momentum premium. The regression results indicate that the equally weighted momentum premium loads positively on market risk and the low beta anomaly and negatively on the low volatility, currency risk and

liquidity premium. Notably, none of the momentum premium factor loadings are significantly different from zero. The GRS statistic rejects the null hypothesis of time-series alphas being jointly equal to zero, further solidifying that neither low beta, low volatility, currency risk nor liquidity adequately explain the equally weighted momentum premium on the JSE.

	Momentum - Market Cap Weighting						
	α	β_{J203}	β_{BAB}	β_{LowVol}	β_{LIQ}	β_{ZAR}	Adj. R^2
1	0.0090	0.8976	0.0387	-0.2626	-0.0683	0.0445	67.18%
	0.0009***	***0.0000******	***0.4433***	***0.0006******	***0.3428***	***0.5117***	
2	0.0002	0.7174	0.3765	-0.1003	-0.0852	0.1818	64.88%
	0.9140	***0.0000******	***0.2448***	***0.1485***	***0.0583****	***0.0000******	
3	-0.0029	0.7940	0.0773	-0.0165	-0.1219	0.1499	68.20%
	0.1884	***0.0000******	***0.0610****	***0.6921***	***0.0438****	***0.0109****	
4	-0.0040	0.6948	0.0368	-0.0821	0.0230	0.2196	59.09%
	0.0845*	***0.0000******	***0.3773***	***0.1097***	***0.6868***	***0.0000******	
5	-0.0079	0.7398	-0.0235	-0.1356	-0.0247	0.1022	58.82%
	0.0037***	***0.0000******	***0.6394***	***0.0161****	***0.7471***	***0.1580***	
1-5	0.0169	0.1578	0.0622	-0.1362	-0.0437	-0.0577	2.39%
	0.0000***	***0.1202***	***0.3089***	***0.1885***	***0.7364***	***0.5563***	
GRS	5.5622						
	0.0002***						

*Table 5.16 Time-series regression results conducted on market capitalization weighted momentum test portfolios using the augmented attribution model that considers low beta, low volatility, currency risk and liquidity. P-values are assigned asterisks based on statistical significance where *,**,*** indicate significance at the 10%, 5% and 1% level.*

Table 5.16 above depicts the results of the time-series attribution regressions conducted on market capitalization weighted momentum test portfolios. Consistent with the equal weighted momentum sorts, portfolio alphas decrease monotonically and consistently when moving from the extreme winner to the extreme loser quintile. The extreme winner portfolio produces a time-series alpha of 0.9% per month, equivalent to 10.79% per annum and is significant at the 1% level. The extreme loser portfolio produces a negative monthly time-series alpha of -0.79% per month, equating to -9.53% per annum and is significant at the 1% level. The zero-cost momentum portfolio produces a time-series monthly alpha of 1.69% per month, equivalent to 20.33% per annum and is significant at the 1% level. Compared to the equally weighted momentum portfolio results, the market capitalization weighted momentum premium achieves an additional monthly premium of 0.07%, equating to an additional 87 basis points per annum on average.

The factor loadings of the market capitalization weighted quintile portfolios are virtually identical to those of the equal weighted momentum sorts. The loadings on the equity market risk premium are all highly significant, with the extreme winner and loser portfolios achieving significant market betas of 0.898 and 0.74 respectively. In fact, all of the quintile portfolios produce market betas in excess of 0.695 and are significant at the 1% level. Once again, portfolios 1 to 4 produce positive factor loadings on the low beta premium while portfolio 5 produces a negative factor loading, implying that higher momentum portfolios produce returns that tend to covary more with lower beta shares than their lower momentum counterparts, yet only Portfolio 3's factor loading is statistically significant and only at the 10% level. The factor loadings on the low volatility premium are more noteworthy, with the extreme winner and loser portfolios loading negatively on the low volatility premium, achieving coefficients of -0.263 and -0.136 respectively. The implication is that both extreme winner and extreme loser shares tend to covary more with high idiosyncratic risk shares. Importantly, when considering the economic size of the factor loadings, the extreme winner portfolio achieves a coefficient that is 1.93 times greater than extreme loser portfolio, implying that of the two portfolios, the extreme winner portfolio constituents tend to be high idiosyncratic risk shares.

The results however are inconsistent with the low volatility premium driving momentum profits on the JSE, as the higher relative volatility of momentum shares does not seem to reduce from the return premium they generate through time. The liquidity factor loadings are largely negative with only Portfolios 2 and 3 producing significant coefficients at 10% and 5% levels respectively. The non-significance of the extreme winner and loser portfolio factor loadings indicate that liquidity, when proxied by turnover, does not seem to explain the momentum premium. Solely considering the sign of the coefficients, the results are inconsistent with the results of Page, Britten and Auret (2013) as momentum portfolios seem to load negatively on liquidity. Further, there does not seem to be any variation in factor loadings across the quintile portfolios, indicating that liquidity is unrelated to the market capitalization weighted momentum premium on the JSE.

It should be noted that negative loadings on the liquidity factor applied in the time-series regressions presented above imply that the momentum premium tends to covary with low liquidity shares. The implication is highly consistent with the findings of Pastor and Stambaugh (2003) where the typical liquidity premium (low liquidity shares minus high liquidity shares) explained more than half of the momentum premium and that momentum loaded positively on less liquid share returns. Unfortunately, the non-significance of the factor loadings presented in Table 5.16 cast doubt on any finite conclusions relating liquidity to momentum returns on the JSE. The factor loadings on the currency risk premium are generally consistent

with those of the equally weighted momentum sorts as all portfolios display positive factor loadings, yet now both portfolios 1 and 5 produce insignificantly positive coefficients. Interestingly, when comparing the currency risk coefficients of portfolios 1 and 5, the extreme loser currency beta is 2.3 times that of the extreme winner, implying that extreme loser shares are relatively more highly exposed to currency risk, however the results are inconclusive given that neither factor loading is statistically significant.

Lastly, considering the factor loadings of the long-short market capitalization weighted momentum premium, the time-series coefficients are highly similar to those achieved by the equally weighted momentum premium presented in Table 5.15. Once again, the factor loadings on the market and low beta premium are positive while the inverse is true for the low volatility, liquidity and currency risk premiums. However, once again, none of the coefficients are significantly different from zero. The results of the GRS test statistic provide additional evidence in rejecting the low beta, low volatility, currency risk and liquidity premiums as determinants or drivers of momentum returns on the JSE. The GRS test statistic strongly rejects the null of time-series alphas being jointly equal zero, implying that the factor model applied fails to explain the market weighted momentum premium on the cross-section of shares on the JSE.

	Momentum - Momentum Rank Weighted						
	α	β_{J203}	β_{BAB}	β_{LowVol}	β_{LIQ}	β_{ZAR}	Adj. R^2
1	0.0123	0.8878	-0.0038	-0.5345	0.0417	0.0601	39.69%
	0.0205*	***0.0000*****	***0.9608***	***0.0000*****	***0.7982***	***0.5950***	
2	-0.0003	0.7040	0.0674	-0.1223	-0.1015	0.1864	60.83%
	0.9137	***0.0000*****	***0.2449***	***0.1035***	***0.0272****	***0.0001*****	
3	-0.0036	0.7792	0.0935	-0.0157	-0.1449	0.1446	63.94%
	0.1202	***0.0000*****	***0.0309****	***0.7222***	***0.0168****	***0.0169****	
4	-0.0043	0.6730	0.0401	-0.0970	0.0188	0.2136	56.57%
	0.0963*	***0.0000*****	***0.4730***	***0.0609****	***0.8220***	***0.0040*****	
5	-0.0081	0.7219	-0.0229	-0.1594	-0.0518	0.1091	57.11%
	0.0031**	***0.0000*****	***0.6583***	***0.0031*****	***0.4559***	***0.1331***	
1-5	0.0204	0.1658	0.0190	-0.3751	0.0935	-0.0489	5.36%
	0.0009**	***0.2889***	***0.8201***	***0.0089*****	***0.6484***	***0.7290***	
GRS	3.9792						
	0.0036**						

*Table 5.17 Time-series regression results conducted on momentum-rank weighted momentum test portfolios using the augmented attribution model that considers low beta, low volatility, currency risk and liquidity. P-values are assigned asterisks based on statistical significance where *,**,*** indicate significance at the 10%, 5% and 1% level.*

Table 5.17 presents the final set of results of time-series attribution regressions run on momentum-rank weighted momentum test portfolios. As with the equal and value weighted results, time-series alphas decrease monotonically when moving from the extreme winner to the extreme loser portfolio. The extreme winner portfolio produces a time-series alpha of 1.23% per month, equivalent to 14.74% per annum and is significant at the 5% level. Conversely, the extreme loser portfolio produces a monthly time-series alpha of -0.812% per month, equating to a loss of -9.76% per annum and is significant at the 1% level. The zero-cost momentum premium, representing the simultaneous long-short investment in the momentum rank weighted winner and loser portfolio produces a monthly time-series alpha of 2.04%, equating to an annualized risk-adjusted return of 24.50% per annum and is significantly different from zero at the 1% level. Consistent with the results of the Fama-French and CAPM specification regressions, the momentum-rank weighted momentum premium supersedes the risk-adjusted excess return of the equal and value weighted momentum quintile portfolios. Under the current model specification, the momentum-rank weighted time-series alpha produces an additional 0.42% and 0.35% per month more than the equal and value weighted momentum premiums, equating to 5.05% and 4.2% per annum on average respectively.

Consistent with the previous regressions, the factor loadings on market premium are economically above 0.7 (barring portfolio 4) and consistently significant at the 1% level. Similarly, the signs of the factor loadings on the low beta premium indicate that Portfolios 2 to 4 tend to mimic the returns on low beta shares, however, only the coefficient achieved by portfolio 3 is statistically significant. The low beta factor loadings on the extreme portfolios are both negative, yet the extreme loser portfolios is economically larger, amounting to -0.023 compared to -0.004 achieved by the extreme winner portfolio.

Considering the factor loadings on the low volatility premium, the results once again are highly similar to those of the equal and value weighted momentum sorts. The sign of the factor loadings are all negative with both the extreme winner and loser portfolios producing statistically significant coefficients of -0.534 and -0.159 respectively. Interestingly, the magnitude of the coefficient on the winner portfolio has increased when compared to the equal and value weighted sorts and is now 3.353 times greater than the idiosyncratic risk factor loading of the loser portfolio. The significance of the factor loadings lends very little credence to the attribution test as the hefty covariance of both the winner and loser portfolios with high idiosyncratic risk share returns fails to explain the time-series alphas, removing the possibility of momentum profits being driven by the low volatility premium.

The factor loadings on the high minus low liquidity premium are the most consistent with recent literature, specifically the findings of Lee and Swaminathan (2000) and Page, Britten and Auret

(2013). For the first time, the winner portfolio produces a positive factor loading of 0.0417, while the loser portfolio a negative -0.0518. The result implies that winner shares tend to covary positively with high liquidity shares while the inverse is true for loser shares. Unfortunately, the positive result is limited to the sign of the factor loadings as neither of the factor loadings on the extreme portfolios are significant, implying that liquidity, when proxied by turnover, fails to explain the momentum premium. The factor loadings on the currency risk premium are virtually identical in terms of magnitude and pattern to those of the equal and market capitalization weighted momentum portfolio sorts. All of the portfolios produce positive factor loadings, yet only Portfolios 2-4 are significantly different from zero. When comparing the extreme portfolio factor loadings on currency risk, the extreme loser coefficient is 1.81 times greater than that of the extreme winner implying that once again, extreme loser shares are more sensitive to currency risk, yet neither are statistically significant.

The factor loadings on the momentum premium portfolio differ slightly to those of the equal and value weighted momentum premiums as only low volatility and currency risk achieve negative factor loadings. Unfortunately, the positive relationships between momentum rank weighted momentum and market beta, the low beta premium and liquidity lack statistical significance. Similarly, the negative factor loading on the currency risk premium implies that the momentum premium loads positively on rend hedge shares yet, the coefficient is statistically insignificant. A notable change relates to the factor loading on the low volatility premium. For the first time, the loading is negative and significant at the 1% level. The implication of the finding entails that momentum returns are highly correlated with the returns on high idiosyncratic risk shares, yet the significantly negative relationship with the low volatility premium fails completely to reduce the momentum premium as the time-series risk adjusted alpha is at its highest when compared to the equal and value weighted premiums. Lastly, the GRS test statistic rejects the null hypothesis joint equivalence of the time series alphas equaling zero at the 1% level, strongly proving that the low beta, low volatility, currency risk and liquidity premium fail to explain the profits achieved by momentum-rank weighted momentum sorts conducted on the cross-section of shares listed on the JSE.

The results of the time-series tests conducted on momentum portfolios using a factor pricing model that considers the low beta, low volatility, currency risk and liquidity premium indicate that momentum profits are significantly positive *ex post* risk-adjustment. Irrespective of the weighting methodology applied, the zero cost momentum premium consistently produces time-series alphas well in excess of 1.5% per month. Much like the CAPM and Fama-French regressions, momentum portfolios consistently achieve economically high and statistically significant market betas. In terms of the low beta premium, winner momentum portfolios tend

to positively load on low beta shares while the inverse relationship applies to extreme loser shares. The result presents a quandary when considering that consistently throughout the regression analysis, the extreme winner portfolios tend to produce the highest market betas.

A possible explanation could be that the majority of winner shares do typically produce higher betas yet a proportion of momentum shares produce return patterns that tend to covary more with the returns on low beta shares. Equally, the low beta premium factor loadings should be interpreted with caution as the majority are not statistically different from zero. The liquidity premium results are equally disappointing, as numerous studies have linked momentum returns to liquidity. As discussed extensively in literature review, there is evidence presented on both sides of the liquidity framework, where some find a positive relationship between liquidity and momentum while others the opposite. In terms of the factor loadings on the defined liquidity premium, only the momentum-rank weighted regressions produce a distinctive relationship (that is aligned to the findings of Page, Britten and Auret (2013)) between liquidity and momentum. Two caveats are in order. Firstly, despite the signs of the coefficients being consistent with evidence presented in literature, none of the results are statistically meaningful. Secondly, and more importantly, the liquidity factor applied in the time-series regression analysis produces a non-existent inverse premium indicating that high liquidity shares outperform their low liquidity counterparts on the JSE. The lack of the liquidity premium augments the uncertainty surrounding the time-series results, but fall beyond the scope of this study.

All of the momentum portfolios produced positive factor loadings on the currency risk premium, implying that all portfolios are more exposed to rand tracker as opposed to rand hedge shares. The finding is logical as one would expect that the majority of shares on the JSE are more exposed to local currency movements, with a relatively smaller proportion being rand hedge shares. The results did however consistently indicate that extreme loser shares tend to load more on the currency risk premium, implying that extreme losers are more likely affected by depreciations in the dollar/ZAR exchange rate. Further proof is portrayed in the zero cost momentum premium attribution regressions, with all of the momentum premiums (equal, value and momentum rank) producing negative factor loadings, implying that the momentum premium seems to offer some form of currency hedge as returns tend to covary more with rand hedge shares. Unfortunately, and like the low beta and liquidity premium, the results should be viewed with caution as the currency risk factor loadings in the extreme portfolios and zero cost momentum premium lack any form of statistical significance.

The only factor that seemed to maintain any form of explanatory power was the low volatility premium, yet, the sign of the factor loading was consistently negative across weighting

specifications for both the extreme winner and loser portfolios. The result therefore implies that although both winner and loser portfolios covary more with high idiosyncratic risk shares, low volatility does not drive momentum profits. Such a result is highly consistent with the findings of McLean (2010) and Page, Britten and Auret (2016) as both found that idiosyncratic risk fails to explain the momentum premium. The idiosyncratic risk factor loadings are evidence in favor of the 'limits to arbitrage' hypothesis as the results indicate that idiosyncratic risk fails to explain the momentum premium. Therefore, consistent with the findings of Page, Britten and Auret (2016), idiosyncratic risk as an arbitrage holding cost fails to effect the momentum premium on the JSE. Lastly, the time-series alphas produced using low beta, low volatility, currency risk and liquidity are economically higher than those produced using the CAPM and Fama-French three factor model. Moreover, there is a further shift in the proportion of the premium earned by the long and short position in the extreme winner and loser shares and is delineated in the table that follows.

Position Contribution	Equal weighting	Value Weighting	Momentum Rank Weighting	Average
Long	51.45%	55.47%	75.75%	60.89%
Short	48.55%	44.53%	24.25%	39.11%

Table 5.18 Relative contribution to risk-adjusted momentum premium using the factor strategy that considers the low beta, low volatility, currency risk and liquidity premium

The relative contribution of the long position in the winner portfolio now provides 60.89% of the momentum premium across weighting specifications, while the short position in the loser portfolio only provides 39.11% of the total premium. The results are in contrast to those of the CAPM and Fama-French based attribution regressions (see Tables 5.6 and 5.10), where the majority of the premium is derived from the short position in the loser portfolio. A potential cause of the result may be due to "bad model" problem defined by Fama (1998), where the current attribution model produces greater time-series alphas due to the fact that it is not an appropriate describer of the data generating process governing share returns or momentum on the JSE.

The plausibility of such an argument is limited as even though liquidity and currency risk do not produce significant factor premiums both the low idiosyncratic risk and low beta phenomenon are significant and positive on the cross-section of shares listed on the JSE, implying that both premiums are deserving of incorporation within a pricing model. Importantly, the results presented above are further evidence in favor of a distinct momentum premium on the JSE, as none of the factors considered thus far are able to explain the cross-sectional variation in portfolio returns sorted on historical cumulative return performance. Additionally, the relative contribution of the long and short momentum position seems sensitive to the

underlying model applied. A corollary finding relates again to the 'limits to arbitrage' hypothesis where the limitations on short selling can potentially result in smart money being unable to fully capitalize on mispricing. The findings indicate that long position provides as much, if not a greater, proportion of the profit related to the momentum strategy, reducing the requirement of a short position to fully capitalize on the momentum premium on the JSE.

5.6 TIME-SERIES TESTS OF MOMENTUM USING THE VAN RENSBURG (2002) ARBITRAGE PRICING FACTORS

The final time-series attribution model to be used in this section is inspired by the work of van Rensburg and Slaney (1997) and van Rensburg (2002). In their seminal paper, van Rensburg and Slaney (1997) found that the JSE Industrials and All-Gold indices were priced sources of risk and therefore satisfied the empirical criterion for inclusion in an APT based asset pricing model for the cross-section of shares listed on the JSE. In March 2000, the JSE industry indices were reclassified, resulting in the original factor pricing model being incongruent with the current indices definitions and inclusion criteria. Van Rensburg (2002) extended the original test to consider the new indices (and sub-indices). Using principal component and factor analysis, the author found that like Slaney and van Rensburg (1997), two principal components explained the majority of the cross-sectional variation in returns on the JSE, implying once more that a two factor model is sufficient. Applying oblique promax rotation, the author found that like van Rensburg and Slaney (1997), factor exposures clustered in financial-industrial and resources independently. The conclusion of the factor analysis was that the Financial and Industrial Index (FINDI or CI21) and the Resources Index (RESI or CI11) are the most consistent proxies for the first two principal components extracted from the covariance matrix of returns on the JSE.

Using the findings of van Rensburg (2002) as a premise, the final attribution model simply applies the excess returns earned by the Financial-Industrial index and the Resources Index (hereafter "FINDI" and "RESI") as factors in explaining the excess returns earned on momentum portfolios. It should be noted that the track record of Ross (1976) APT inspired factor models explaining the momentum premium is as poor as the CAPM and other anomaly/mispricing based models. Griffin, Ji and Martin (2003) employed the Chen, Roll and Ross (1986) risk factors in attempt to explain the global momentum premium. The authors found that actual momentum profits were approximately 0.67% per month on average while the unconditional APT model predicted momentum returns of -0.03% per month. The 0.7% difference in returns was significant at the 5% level, indicating that the APT model, using the Chen, Roll and Ross (1986) factors was unable to explain the global momentum premium.

Van Rensburg (2001) conducted an in-depth study on stylistic mispricing on the JSE where stylistic anomalies were tested gross and net of risk. The risk-adjustments applied were the conventional market model and the augmented market model inspired by Slaney and van Rensburg (1997). The author found that the application of the APT like factor model actually increased the time-series alphas achieved by the momentum portfolios when compared to those produced by the pure market model time-series attributions. The most promising evidence of APT factor explaining the momentum premium was conducted by Ahn, Conrad and Dittmar (2003) where the authors applied a non-parametric GMM specification using industry factor portfolios. The authors found that when using the non-parametric benchmarks, momentum profits declined by approximately 50% when compared with raw gross returns, implying that a non-parametric risk based application of an unconstrained APT effectively explained more than 50% of the momentum premium.

The following set of tests are effectively identical to the CAPM based regressions discussed in section 5.3, yet now the explanatory variables are the FINDI and RESI excess return indices over the period January 1997 to September 2015. Both indices are value-weighted and adjusted for corporate actions such as dividends, unbundling's and consolidations. The monthly returns of both indices are measured in excess of the 90-day Treasury bill rate. Once again, the time-series attribution model is applied against three variants of momentum, namely equally weighted, value weighted and momentum rank weighted momentum portfolios. For each set of regressions, the time-series alphas, factor loadings and adjusted R^2 values are described as well as the GRS statistic for each set of regressions. The results of the time-series regressions using the van Rensburg (2002) APT factors are presented in the tables that follow.

	Momentum - Equal Weighting			
	α	β_{FINDI}	β_{RESI}	Adj. R^2
1	0.0070	0.6579	0.1954	57.16%
	0.0486**	**0.0000*****	**0.0044*****	
2	0.0016	0.6710	0.0249	63.38%
	0.5158	***0.0000******	***0.4926***	
3	-0.0004	0.6667	0.0730	65.15%
	0.8555	***0.0000******	***0.0375*****	
4	-0.0005	0.7666	-0.0147	66.46%
	0.8366	***0.0000******	***0.6800***	
5	-0.0066	0.6364	0.1355	58.80%
	0.0193**	***0.0000******	***0.0000******	
1-5	0.0136	0.0215	0.0599	0.41%
	0.0005***	***0.8604***	***0.4559***	
GRS	3.7561			
	0.0056***			

*Table 5.19 Time-series regression results conducted on equally weighted momentum test portfolios using the van Rensburg (2002) APT factor attribution model. P-values are assigned asterisks based on statistical significance where *,**,*** indicate significance at the 10%, 5% and 1% level.*

The results of the equally weighted momentum time-series regressions are presented in Table 5.19. Consistent with the previous time-series regression tests, the momentum portfolios produce time-series alphas that decrease monotonically when moving from the extreme winner to the extreme loser quintile. The extreme winner portfolio (Portfolio 1) produces a risk adjusted excess return of 0.7% per month, equivalent to 8.42% per annum and is significant at the 5% level of significance. The extreme loser portfolio produces a risk-adjusted alpha of -0.66% per month, equivalent to an annual loss of -7.87% per annum and is significant at the 5% level. The equally weighted excess momentum premium achieves a time-series alpha of 1.36% per month, equating to a risk-adjusted average return of 16.28% per annum and is significant at the 1% level. The factor weightings of the equally weighted momentum portfolios provide insight into sector exposure of momentum shares but fails to explain the equally weighted momentum premium on the JSE.

The factor loadings of the extreme winner portfolio indicate that winner shares tend to load significantly on both FINDI and RESI shares. Importantly, size of the factor loadings indicate that the FINDI coefficient is 3.4 times greater than the RESI coefficient. Furthermore, the extreme loading on the FINDI excess returns is consistent across momentum portfolios, with all portfolios achieving coefficients in excess of 0.6 which are consistently significant at the

1% level. The loser portfolio also tend to load heavily on the FINDI and RESI excess returns, with both coefficients being significant at the 1% level. The results therefore imply that both winner and loser shares tend to load significantly on both factors, but both factors fail to explain the source of momentum profits or the momentum premium.

The results are summarized in the factor loadings of the zero cost winner minus loser equally weighted excess return portfolio, where both factors achieve positive weightings, yet are statistically insignificant. The conclusion is reiterated by the results of the GRS test statistic which rejects the null of time-series alphas being jointly equal to zero at the 1% level of significance. The implication is therefore that the APT factors of van Rensburg (2002) fail to explain the excess returns of equally weighted momentum portfolios on the cross-section of shares listed on the JSE.

	Momentum - Value Weighting			
	α	β_{FINDI}	β_{RESI}	Adj. R^2
1	0.0079	0.6578	0.2193	59.45%
	0.0228*	***0.0000****	***0.0015****	
2	0.0021	0.6820	0.0349	67.28%
	0.3657	***0.0000****	***0.3030***	
3	0.0003	0.6847	0.0806	69.86%
	0.9079	***0.0000****	***0.0175****	
4	0.0000	0.7814	-0.0031	68.66%
	0.9850	***0.0000****	***0.9293***	
5	-0.0064	0.6446	0.1543	60.71%
	0.0212*	***0.0000****	***0.0007****	
1-5	0.0143	0.0131	0.0650	0.36%
	0.0004*	***0.9156***	***0.4657***	
GRS	3.5842			
	0.0078*			

*Table 5.20 Time-series regression results conducted on market capitalization weighted momentum test portfolios using the van Rensburg (2002) APT factor attribution model. P-values are assigned asterisks based on statistical significance where *,**,*** indicate significance at the 10%, 5% and 1% level.*

The results of the time-series attribution regressions conducted on value weighted momentum portfolios shown in table 5.20 above are effectively identical to those presented in Table 5.19. Once again, the momentum effect is consistent even after accounting for factor risks as the highest time-series alpha is achieved by the extreme winner portfolio (Portfolio 1) after which portfolios alphas decrease monotonically when moving to the extreme loser portfolio (Portfolio

5). The extreme winner portfolio achieves a time-series alpha of 0.79% per month, equivalent to 9.43% per annum and is significant at the 5% level while the extreme loser portfolio achieves a monthly time-series alpha of -0.64%, equivalent to an annualized loss of 7.73% and is significant at the 5% level.

The zero cost market capitalization weighted risk-adjusted momentum premium is 1.43% per month, equivalent to 17.16% per annum and is significant at the 1% level. The results indicate that neither the excess returns on the FINDI nor RESI explain the market capitalization weighted momentum strategy applied on the cross-section of shares listed on the JSE. The factor loadings on the momentum portfolios are virtually identical to those estimated assuming equal weighted momentum portfolios. Once again, the factor loadings on the FINDI are consistently positive, in excess of 0.64 and significant at the 1% level. Similarly, the loadings on the RESI are generally positive but only significant for the extreme winner and loser portfolios at the 1% level.

The variation in factor loadings is relatively muted, with the FINDI coefficients being identical for both the extreme winner and loser portfolios, while the RESI coefficient of the extreme winner portfolios is 1.4 times greater than that of the extreme loser. Further, the FINDI coefficients are consistently larger than those of the RESI coefficients of the extreme portfolios, possibly implying that both winner and loser shares tend to covary more with financial and industrial shares as opposed to mining counters. A more plausible explanation could relate to the current aggregate company profile of the JSE, which has shifted from a predominantly mining and resource based exchange to a majority financial and industrial based index. The time-series coefficients of the market capitalization excess return portfolio provide evidence that the van Rensburg (2002) APT factors fail to explain the momentum premium on the JSE.

Both the FINDI and RESI factor loadings are positive, but neither are statistically significant, implying that industry or sector risk premiums do not drive momentum on the JSE. The result is further confirmed via the GRS test statistic, with the null of portfolio alphas being jointly equal to zero is rejected at the 1% level, indicating that the factor model considered cannot explain the profits achieved via a market capitalization weighted momentum sort conducted on the cross-section shares listed on the JSE. Lastly, as shown throughout the chapter, market capitalization weighted momentum tends to marginally outperform equally weighted momentum on a risk-adjusted basis, achieving an additional 0.07% per month or 0.87% per annum which is solely attributable to weighting.

	Momentum - Momentum Rank Weighting			
	α	β_{FINDI}	β_{RESI}	Adj. R^2
1	0.0079	0.5997	0.2852	28.89%
	0.1751	***0.0000****	***0.0053****	
2	0.0013	0.6663	0.0267	62.24%
	0.6000	***0.0000****	***0.4587***	
3	-0.0005	0.6670	0.0687	64.92%
	0.8301	***0.0000****	***0.0499****	
4	-0.0005	0.7680	-0.0129	66.54%
	0.8208	***0.0000****	***0.7201***	
5	-0.0070	0.6307	0.1425	58.30%
	0.0143*	***0.0000****	***0.0009****	
1-5	0.0149	-0.0311	0.1426	0.89%
	0.0178*	***0.8380***	***0.2004***	
GRS	2.9605			
	0.0255*			

*Table 5.21 Time-series regression results conducted on momentum rank weighted momentum test portfolios using the van Rensburg (2002) APT factor attribution model. P-values are assigned asterisks based on statistical significance where *,**,*** indicate significance at the 10%, 5% and 1% level.*

The results of the momentum-rank weighted time-series attribution regressions are presented in Table 5.21. The results of the time-series regressions show that, once again, the van Rensburg (2002) APT factors fail to explain the excess returns of a momentum-rank weighted strategy applied on the cross-section of shares listed on the JSE. The extreme winner portfolio (Portfolio 1) produces a time-series alpha of 0.79% per month, equivalent to 9.54% per annum. Interestingly, even though the time series alpha is economically the largest of the three weighting categories (compared to 0.701% and 0.786% achieved by the equal and value weighted long only portfolios), the intercept is statistically insignificant, achieving a p-value of 0.175. As expected, the portfolio time-series alphas decrease monotonically when moving from the extreme winner to extreme loser portfolio, with the extreme loser portfolio producing a time-series alpha of -0.7%, equating to an annualized loss of -8.37% and is significant at the 5% level.

The zero cost momentum-rank weighted portfolio produces a time-series risk-adjusted excess return of 1.49% per month, equating to an annualized risk-adjusted return of 17.91% and is significant at the 5% level. Like the equal and value weighted momentum test portfolios, the results presented plainly dictate that the van Rensburg (2002) industry based risk factors fail to explain the momentum premium on the JSE and that the result is not driven by weighting methodology.

As noted previously, the momentum excess returns across weighting mechanisms varies with the momentum-rank weighted premium producing an additional annual return of 1.63% and 0.76% over the equal and value weighted momentum premiums. The results therefore consistently point to the momentum rank weighting methodology being the most profitable weighting mechanism when conducting momentum strategies on the cross-section of shares listed on JSE. Analysis of the factor loadings further points to the inability of the excess returns on the FINDI and RESI being able to explain the variation in time-series alphas of the momentum rank weighted test portfolios. Again, the factor loadings on the FINDI are all consistently positive, above 0.6 and significant at the 1% level.

Similarly, both the extreme winner and extreme loser portfolios achieve significantly positive factor loadings (at the 1% level) on the RESI excess return factor, with the extreme winner portfolio factor loading being twice as large as that of the extreme loser, indicating that the winner shares tend to covary more with resources and mining sector returns. The lack of differentiation in the factor loadings, specifically with respect to the extreme winner and loser portfolios further indicates that neither the FINIDI nor RESI are capable in explaining the variation in momentum test portfolios. Lastly, the GRS test statistic rejects the null of portfolio alphas being jointly equal to zero at the 5% level of significance, providing more evidence against the van Rensburg (2002) APT factors ability in explaining momentum returns.

The application of the van Rensburg (2002) factors results in similar findings to those produced when applying the CAPM, Fama-French, low beta, low idiosyncratic, currency risk and liquidity attribution models. The model however is more similar to the low beta, low idiosyncratic risk, currency risk and liquidity model, specifically when considering the relative contribution of the long and short components of the momentum premium. The position percentage contribution to the time-series alphas estimated using the van Rensburg (2002) APT factors is depicted in the table that follows.

Percentage Contribution	Equal Weighting	Value weighting	Momentum Rank Weighting	Average
Long	51.68%	54.95%	53.25%	**53.29%**
Short	48.33%	45.04%	46.75%	**46.71%**

Table 5.22 Relative contribution to risk-adjusted momentum premium using the factor strategy that considers the van Rensburg (2002) APT factors

Table 5.22 above dictates the long and short position contribution to the momentum premiums for the equal, value and momentum rank weighted momentum strategies. Unlike the CAPM and Fama-French attribution models, the percentage contribution of the long position in winner shares is 53.29% on average, thereby dominating the percentage contribution of the short

position in loser shares. Interestingly, unlike the previous attribution models considered, table 5.22 indicates that the van Rensburg (2002) APT factor model produces risk-adjusted momentum excess returns that result in the value weighted premium winner shares dominating the equal and momentum rank weighted winner contributions to overall alpha (55.95% compared to 51.68% and 53.25% achieved by the equal and momentum rank weighted risk-adjusted momentum premiums).

The results therefore cast doubt on the findings of Lesmond *et al.* (2004) as only two of the attribution models (CAPM and Fama-French) produce time-series alphas that depict the majority of the risk-adjusted momentum premium being dominated by the short position in loser shares, further implying that the relative contribution of the long and short positon seems highly sensitive to the attribution model applied. The GRS tests indicate that the validity of the models are all effectively similar as none are able to systematically explain the momentum premium on the JSE and furthermore, all factors utilized produce return premiums, barring the liquidity, currency risk and size factors. A further implication is that on the cross-section of shares listed on the JSE, the risk-adjusted momentum excess return premium is made up of equal return contributions from the long and short position in winner and loser shares.

5.7 STEPWISE REGRESSIONS USING ALL FACTORS CONSIDERED

The final test will allow for the inclusion of all the time-series factors utilized within in a single regression framework. The purpose of the final tests is twofold. Firstly, the benefit of stepwise regression analysis is that it allows for the determination of key explanatory variables (factor premiums) that explain/drive variation in the dependent variable (momentum portfolio returns). Secondly, assuming backward elimination, the final set of explanatory variables will define a parsimonious model for each test portfolio, possibly reducing alpha and therefore explaining the momentum premium on the cross-section of shares listed on the JSE. Unfortunately, the stepwise regression methodology removes the possibility of calculating a GRS test statistic as the F-test requires a pre-defined set of explanatory variables in order to calculate the appropriate degrees of freedom with the obvious issue being that each momentum portfolio will have varying values of N explanatory factors. Prior to discussing the results of the stepwise regressions, a basic description of the methodology is required. Considering a trivial time-series linear regression specification described below:

$$R_{i,t} - r_f = \alpha_i + \sum_{j=1}^{L} \beta_{i,j} X_{j,t} + \varepsilon_{i,t} \qquad (5.10)$$

$$R_{i,t} - r_f = \alpha_i + \sum_{j=1}^{L*} \beta_{i,j} X_{j,t} + \varepsilon_{i,t} \qquad (5.11)$$

The initial matrix $X_{j,t}$ is assumed to contain all of the factor premiums considered, therefore the excess return of the J203 ALSI, size, value, low beta, low idiosyncratic risk, currency risk, liquidity and excess returns on the FINDI and RESI. Backward elimination implies that the initial set of factors is equal to *L* and is then reduced in steps where *L* decreases to the optimal number of factors based on a benchmark elimination factor such as p-value greater than 10%. The final regression will only consider *L** factors where the said factors are assumed to maintain the highest level of explanatory power relative to the excess returns on the momentum test portfolio. An obvious and expected result is that *L**<*L* for each of the attribution regressions. The results of the Stepwise regressions are displayed in the table that follows. Importantly, the results displayed represent the stepwise regressions run on the market capitalization weighted momentum test portfolios. The results of the stepwise regressions run on the equal weighted and momentum rank weighted momentum portfolios are virtually identical and are presented in the Appendix 1f and 1g. For the purpose of tractability, only the results of the market capitalization weighted momentum portfolios are discussed.

Table 5.23 presents the results of the time-series stepwise regressions using all of the factor premiums utilized across the various attribution models. The results portrayed above are surprising. Firstly, the inclusion of all factors and the application of backward elimination seems to increase the momentum effect, which is incongruent with the logical outcome of lower alphas given more explanatory variables. Without considering the balance between parsimony and explanatory power, the results indicate that the inclusion of more explanatory variables seems to increase the risk-adjusted excess returns earned by the market capitalization weighted momentum strategy. Considering the extreme winner portfolio, the monthly risk-adjusted return is 1.54% per month, equating to a long-only annualized alpha of 18.5% and is significant at the 1% level.

The implication of the result is that under the least parsimonious attribution model, the pure long-only momentum investment produces risk-adjusted excess returns that are greater than the majority of the long-short momentum factor premiums displayed in the sections above. Similarly, the extreme loser portfolio produces a time-series monthly alpha of -1.7%, equating to an annualized loss of 20.45% per annum and is significant at the 1% level. The long-short momentum portfolio produces a risk-adjusted excess return premium of 3.04% per month, equating to a massive 36.54% per annum and is significant at the 1% level. The results reiterate the evidence presented above and are consistent with the findings of Jegadeesh and

Titman (2002). The effects of risk-adjustment seem to exacerbate the momentum effect, to the point that risk-adjusted returns are significantly greater than their equivalent gross unadjusted nominal portfolio returns. The effect is seen in the extreme in Table 5.23. Per the findings presented in Chapter Three where univariate momentum sorts were conducted, the highest market capitalization weighted momentum premium was approximately 1.482% per month, implying an annualized momentum premium of 17.78%. A simple comparison indicates that the effect of risk-adjustment increases the momentum premium by a factor of 2.05.

Turning attention to the factor loadings for each portfolio, the results are partially consistent with those of the individual attribution tests. The extreme winner portfolio attribution regression indicates that five of the nine factor premia (six pricing anomalies and three indices) considered are significant determinants of extreme winner share returns. As with the findings presented in previous sections of this chapter, the factor loading on the J203 ALSI excess return is significantly positive and economically large, achieving a market beta of 1.99. However, the inverse outcome is observed for the van Rensburg (2002) APT factors. Contrary to the regression results presented Table 5.20, both the factor loadings on the FINDI and RESI are significantly negative.

The factor loading on the low volatility premium is also significantly negative, consistent with the results presented in Section 5.5, implying that winner shares covary with the returns on high idiosyncratic risk shares and are therefore more likely to be high idiosyncratic risk shares. Similarly, the factor loading on the small size premium is significantly positive, consistent with the results presented in Section 5.4, implying that winner shares produce returns that covary more with small and medium capitalization shares rather than large capitalization shares. The results indicate that a large number of factors considered in this chapter maintain a significant relationship with extreme winner shares even in a multivariate setting, however, as mentioned, a combination of factors actually seems to have an inverse effect in terms of explaining momentum. The five factor risk-adjusted excess return (time-series alpha) is by far the highest seen throughout the chapter, implying that risk adjustment not only fails to explain the momentum premium but exacerbates it!

The factor loadings of the extreme loser portfolio (rows 10 and 11 of table 5.23) indicate that extreme loser shares tend to load positively on FINDI and RESI shares, where both coefficients are positive and significant at the 1% level. Interestingly, the factor loading on the J203 ALSI is insignificant and therefore culled from the attribution regression.

Portfolio	α	β_{J203}	β_{FINDI}	β_{RESI}	$\beta_{Low\ Beta}$	$\beta_{Low\ Vol}$	β_{Size}	β_{Value}	$\beta_{Liquidity}$	β_{ZAR}	Adj. R^2
Winner	0.0154	1.9975	-0.4828	-0.4311		-0.1037	0.3730				77.15%
	0.0000***	***0.0000******	***0.0023******	***0.0000******		***0.0384****	***0.0000******				
2	0.0032	1.2047		-0.3434			0.2598				78.15%
	0.0455*	***0.0000******		***0.0000******			***0.0000******				
3	-0.0008	1.2720		-0.3175		0.1108	0.2489	0.1125	-0.0997		78.75%
	0.6462	***0.0000******		***0.0000******		***0.0038******	***0.0000******	***0.0081******	***0.0173****		
4	-0.0097	0.2836	0.6318				0.3007				71.98%
	0.0000***	***0.0000******	***0.0000******				***0.0000******				
Loser	-0.0170		0.7071	0.2313			0.3088				65.39%
	0.0000***		***0.0000******	***0.0000******			***0.0000******				
WML	0.0304	1.8948	-1.1475	-0.6300							11.20%
	0.0000***	***0.0000******	***0.0000******	***0.0000******							

*Table 5.23 Time-series stepwise regressions (assuming backward elimination) conducted on market capitalization weighted portfolios using the excess returns on the J203, FINDI, RESI, size, value, low beta, low idiosyncratic risk, currency risk and liquidity factor premiums. P-values are assigned asterisks based on statistical significance where *,**,*** indicate significance at the 10%, 5% and 1% level.*

Lastly, the only other factor premium that seems to explain the returns achieved by extreme loser shares is the small size effect, implying that extreme loser shares also tend to covary with the returns of small and medium capitalization shares. The results are of interest, specifically relating to the factor loadings on the J203, FINDI and ALSI. Van Rensburg (2002) found that the FINDI and RESI tend to explain a large proportion of the cross-sectional variation in share returns listed on the JSE, to the point that both factors supersede the J203 as a proxy for the market portfolio. However, the current composition of the J203, specifically the top forty shares based on market capitalization, fall into the broad categories of financial, Industrial and mining companies, implying that there is a high level of probability for multicollinearity between the J203, FINDI and RESI. In order to determine the level of collinearity, a coefficient variance decomposition is conducted on an equation estimated by regressing the extreme winner and loser portfolios on the J203, FINDI and RESI. The Eigen vector condition values and variance decomposition proportions indicate that there is a high level of multicollinearity between the J203 and the FINDI and RESI.

The final row depicts the stepwise regression for the zero cost long-short winner minus loser market capitalization portfolio. Three of the nine factor loadings remain significant after backward elimination and indicate that the momentum premium maintains a significantly positive relationship with the JSE ALSI and a significantly negative relationship with the excess returns on the FINDI and RESI, however, the significance of the factor loadings is potentially clouded by the high levels of collinearity between the remaining significant explanatory variables as described by the results of the multicollinearity test conducted above. The results of the momentum premium regression further produce a relatively high adjusted R^2 of 11.2%, however neither the significant factors nor the high level of explanatory power reduce the market capitalization momentum portfolio excess returns.

5.8 CHAPTER SUMMARY

In conclusion, the final set of results summarizes the key finding of the chapter succinctly, albeit in an extreme fashion. Irrespective of the risk-adjustment or attribution model applied to the three momentum weighting methodologies, momentum portfolios always produce time-series alphas that decrease in a monotonic fashion when moving from the extreme winner to the extreme loser portfolio. The result is further confirmed via the GRS tests applied to each of the time series attribution regressions, where the null of time-series alphas being jointly equivalent to zero is rejected consistently at the 1% level of significance, with only the momentum rank weighted attribution regressions run using the van Rensburg (2002) factors rejecting the null at the 5% level. Furthermore, irrespective of weighting methodology applied,

the momentum premium is consistently positive, in excess of 1% per month and significant at the 1% level. A secondary finding applies to the weighting methodology, where of the three, the momentum rank weighting method consistently produces the highest risk-adjusted time-series alphas.

The results of the market model (CAPM) attribution regressions are consistent with international evidence as market betas are consistently positive, economically high and statistically significant across momentum portfolios, irrespective of the portfolio weighting methodology applied. Consistent with the results of Jegadeesh and Titman (1993, 2001), market beta fails to explain the momentum premium on the cross-section of shares listed on the JSE. Additionally, the results further indicate that consistent with the findings of Lesmond *et al.* (2004), when applying a CAPM based attribution model on momentum portfolios, approximately 62% of achieved portfolio alpha emanates from the short position in the loser portfolio. Additionally, even though portfolio factor loadings follow an identical pattern across the portfolio weighting methodologies, the momentum rank weighting methodology produces the highest levels of portfolio alpha, achieving a monthly risk-adjusted return of 1.62% per month, equivalent to an annualized average excess return of 19.4% which is significant at the 1% level.

The results of the Fama-French (1993) three factor model attribution regressions depict results that are highly consistent with international literature, specifically Fama and French (1996) as well as Jegadeesh and Titman (2001) as momentum portfolio excess returns increase when compared to the pure CAPM attribution results. Consistent with the market model attribution results, portfolio alphas increase across weighting methodologies with the momentum rank weighted portfolios consistently outperforming their equal and market capitalization weighted counterparts, achieving a risk-adjusted excess return of 1.77% per month, equating to an average annual return of 21.24% and is significant at the 1% level.

Interestingly, given the fact that the size premium seems to have largely diminished on the JSE, all of the momentum portfolios load positively on the size factor. Importantly, the variation in the size factor loadings indicate that extreme winner shares tend to load more on small and medium shares than their extreme loser counterparts. The findings are consistent with those of Jegadeesh and Titman (2001) as the authors found that both winner and loser shares tend to load positively on the size premium. The momentum portfolio factor loadings on the value premium are consistent with the assertions of Asness (1997) as winner shares produce economically larger negative factor loadings than extreme losers, implying that winner shares are more likely to be growth shares. The results of the Fama-French attribution regressions depict a virtually identical picture to those of the CAPM attribution regressions as neither size

nor value are able to reduce or explain the momentum premium on the cross-section of shares listed on the JSE.

The results of the third set of attribution regressions are unique to both international and local literature as the factor premiums utilized as explanatory variables are relatively unexplored when compared to the CAPM of Fama-French three factor model. The model applied considers the factor premiums based on low volatility, low beta, currency risk and liquidity. Once again, the momentum rank weighting methodology produces the highest levels of portfolio alpha when compared to the equal and value weighted momentum portfolio sorts. The results indicates that the only factor that seemed to maintain any significant explanatory power is the low volatility premium. Across the weighting methodologies, winner shares seem to negatively covary with the low volatility premium implying that extreme winner shares are more likely to be high idiosyncratic risk shares. The results are consistent with those of McLean (2010) and more recently, Page Britten and Auret (2016) as both studies found that the limits to arbitrage hypothesis fails to explain the momentum premium. The results presented are similarly consistent as even though winner shares tend to load more on high volatility shares, the effect does not minimize the momentum premium. In fact, the excess return alphas are greater than those estimated using the CAPM and Fama-French three factor models.

The fourth and final attribution model applied the APT factors prescribed by van Rensburg (2001). The results of the attribution regressions that applied the excess returns on the FINDI and RESI sector indices produced results consistent with those of the prior three attribution regressions as neither the FINDI nor RESI are able to explain the variation in momentum portfolio returns. Interestingly, the results indicated that momentum sorted portfolios displayed minimal levels of variation in terms of their FINDI factor loadings with both extreme winner and loser portfolios achieving significantly positive time-series betas, irrespective of the weighting methodology applied. The momentum portfolio factor loadings did however display a greater level of variation in relation to excess returns on the RESI where the extreme winner portfolios consistently achieved economically higher factor loadings than their extreme loser counterparts. The results are somewhat consistent with the historical performance of resources over the sample period, experiencing both extreme bull and bear markets and therefore producing both significant winner and loser shares, potentially causing the significantly positive factor loadings in both the extreme portfolios. The results therefore imply that over the sample period, winner shares tended to maintain a stronger covariance structure with the resource bull markets. Notably, the results of the final set of attribution regressions produced a consistent outcome with the prior evidence presented as neither the excess

returns on the FINDI and RESI sector indices are able to explain the cross-sectional variation in momentum portfolio returns.

Lastly, the final set of attribution regressions considers all of the factors simultaneously within a stepwise time-series regression. The penultimate outcome consistent with all the previous attribution model results is that irrespective of the set of explanatory variables applied, none of the non-momentum factors are able to explain the momentum premium on the JSE. A more interesting finding relates to the performance of the momentum portfolios within the stepwise framework. A stepwise regression, by design, is an optimization procedure that selects an optimal set of regressors that meet a pre-defined benchmark explanatory criteria. The expectation therefore was that of the non-momentum factors applied, the most significant set of explanatory variables per regression are found and therefore are the most likely to explain, and thereby reduce, the momentum premium. The results presented displayed an opposite effect as the application of the most significant regressors actually resulted in the highest and lowest portfolio alphas for the extreme winner and loser portfolios respectively. The risk-adjusted excess momentum return premium amounted to 3.04% per month, equating to 36.54% per annum, the highest achieved throughout the time-series attribution test. The implication of the results of the step-wise regression are in fact twofold. Firstly, the regression results indicate that, unequivocally, non-momentum factors fail to explain the momentum premium on the JSE. Secondly, and more importantly, the risk-adjusted momentum premium seems to maintain a positive relationship with the number of non-momentum regressors applied within the attribution regression as excess returns increase given the number of non-momentum factor premiums applied as regressors.

A further notable finding relates to the practical long-short components of the momentum premium. The relative contribution of the long and short position in extreme winner and loser shares is highly topical, where Lesmond *et al.* (2004) found that the majority of the excess return achieved via momentum strategies is driven by the short position in the extreme loser portfolio. The results presented above are inconsistent with the finding as only two of the four attribution models applied (CAPM and Fama-French) resulted in the short position in the extreme loser shares producing a larger proportion of alpha. Conversely, the low beta, volatility, currency risk and liquidity model and the van Rensburg (2002) APT factors produce time-series alphas that are largely driven by the long position in the extreme winner portfolios, implying that long-only momentum strategies are feasible on the JSE, even post risk-adjustment.

The results presented prove, unambiguously, that the addition of explanatory variables or factor premiums within an attribution framework does not in any way reduce the momentum

premium on the JSE. In fact, the inverse is true as the results indicate that higher the number of explanatory variables applied, the greater the level of risk-adjusted return. The implication is therefore twofold. Firstly, the results of Fama and French (1996) seem to hold on the cross-section of shares listed on the JSE as the momentum premium cannot be explained using non-momentum factor strategies. Secondly, the lack of a momentum factor within an attribution model will produce nonsensical results as risk-adjustment produces higher returns than gross, non-risk adjusted returns applied on the same strategy.

The results presented within the chapter prove that the application of other non-momentum factor premia on the JSE fails to explain the momentum premium. The outcome therefore entails that the exclusion of momentum from an attribution model results in model misspecification, which is not corrected by incorporating a surplus of non-momentum factor premiums. In order to truly and definitively test whether momentum is a priced factor that explains the cross-sectional variation in share returns on the JSE, the next chapter will test whether momentum is actually priced by applying Fama-Macbeth style panel data cross-sectional regressions. If momentum is indeed priced, then the momentum style passes all tests necessary for inclusion in a factor-pricing model specific to explaining and estimating equity returns on the JSE. The tests conducted above (multivariate) and in the previous chapter (bivariate) prove that the variation in returns achieved by portfolios sorted on historical momentum cannot be explained by a multitude of pricing factors, indicating that momentum is distinctively independent, significant and present on the JSE. The chapter that follows will augment the results that have been described thus far in order to ascertain whether momentum itself is a significant explanatory factor for share returns on the JSE.

CHAPTER SIX: CROSS-SECTIONAL TESTS OF MOMENTUM ASSUMING A SHARE-BY-SHARE AGGREGATION

6.1 INTRODUCTION

The final chapter of this study extends the test presented in Chapter Five to consider whether medium term momentum in share prices contributes to the cross-sectional variation in returns on the JSE. Like Chapter Five, the current chapter's test is multivariate and considers the non-momentum factors applied throughout the study, namely; size proxied by market capitalization, value proxied by the book-to-market ratio, liquidity proxied by turnover, momentum proxied by the six minus one month cumulative return, ex-ante market risk proxied by liquidity adjusted market beta, volatility proxied by ex-ante idiosyncratic risk and currency risk proxied by ex-ante Rand beta. The core empirical difference is that, unlike Chapter Five, momentum is no longer the dependent variable but rather an independent explanatory variable. The procedure applied within the chapter differs to typical tests used for explaining the relationship between factor risks and share returns; specifically those conducted using Fama and Macbeth (1973) two-pass regressions. The two-pass regression methodology implies the initial estimation of time-series betas using pre-defined portfolio returns and excess returns achieved on the respective factors (first pass regressions). Time-series betas are then cross-sectionally regressed on the excess returns achieved by the respective portfolios, assuming a zero constant in order to calculate the factor 'risk' premiums attached to the respective stylistic factors applied (second-pass regression).

The two-pass regression methodology is not applied in this study for the following reasons. Firstly, the purpose of the chapter is to specifically determine whether momentum on the JSE drives the variation in share returns assuming a multivariate test setting. The key outcome is therefore of an explanatory nature and not the determination of factor risk premia or an equity specific South African asset pricing model. Secondly, the JSE is notoriously small in terms of the investable universe of shares based on liquidity constraints and the limited number of listed shares. The two-pass regression methodology requires the sorting of shares initially and simultaneously into portfolios based on the factors to be tested. The constrained universe of shares therefore limits the number of factors that can be simultaneously tested. Similarly, a number of studies find fault with the Fama-Macbeth methodology, specifically relating to the preconceived sorting criteria and potential error-in-variable problems related to the dilution of share-level information clouded through portfolio construction.

Roll (1977) conjectured that portfolio formation based on pre-conceived sorting criteria may result in the concealment of stock-level variation due to the effect of averaging. The effect is

obviously further compounded by the in-portfolio equal weighting which is largely espoused by literature, examples of which are Fama and French (1996) and Chen, Roll and Ross (1987). Lo and Mackinlay (1990) stated that the determination of factor premia via two-pass regression analysis that relies on initially sorting on the testable factors amounts to 'data snooping'. The reasoning is logical as a researcher is testing a known effect, sorting on the effect and then constraining portfolios in the second-pass regression, almost always resulting in the rejection of the null of "no cross-sectional effect". The *a priori*' knowledge of the factor premium, coupled with the non-random nature of initial sorting on the said criteria reduces the power of the test and therefore potentially increases the probability of a Type 1 error, i.e. incorrectly rejecting the null of no cross-sectional effect.

More recently, Shanken and Weinstein (2006) considered the APT factor test conducted by Chen, Roll and Ross (1989) and found that the determination and identification of factor premia is highly sensitive to the procedure initially applied in sorting portfolios. The result therefore casts additional doubt on the two-pass regression methodology as a simplistic variation in the construction of factor portfolios may result in the identification or non-identification of factor premiums that drive share returns.

Lastly, in reference to the question of an investable universe, the current number of listed shares on the JSE, after considering liquidity and price impact constraints, implies that a researcher is limited in the number of factors that can be simultaneously considered when attempting to describe factor premiums that drive share returns. Consider the determination of a four-factor Carhart (1997) model, assuming a $33^{rd}/66^{th}$ percentile split. The required portfolio construction would imply a three by three by three sort, implying 27 test portfolios. A simple requirement for the underlying shares is liquidity, as described by McLelland, Wright and Auret (2014), as first pass time-series regression coefficients will be significantly biased by non-synchronous trading. Assuming that the investable universe of shares on the JSE is 300, the average number of shares per portfolio assuming three factors would be 11, potentially resulting in noisy time-series coefficients and portfolio returns with extreme levels of firm-specific risk. The unfortunate result implies that any analysis beyond three factors is not feasible on the JSE, assuming the utilization of the Fama-Macbeth two-pass regression methodology. The proposed methodology is delineated in the section that follows.

6.2. DATA AND METHODOLOGY

The proposed methodology that allows for the mitigation of potential empirical and experimental issues related to the two-pass regression procedure described above is a share-by-share cross-sectional regression utilizing the priced factors considered within the study.

The share-by-share approach is unique to this study as there is no required portfolio formation applied to the data. Liquidity is of paramount of importance, as illiquidity would bias results without the mitigating benefit of portfolio averaging. In order to ensure a traded liquid universe of cross-sectional individuals (shares), the methodology implies focusing on a constrained set of highly liquid shares on the JSE over the period January 1997 to June 2015. The liquidity of the universe is determined semi-annually where shares are ranked (in descending order) based on market capitalization and average monthly value traded over the previous twelve months. Consistent with the methodology employed by Muller and Ward (2013) shares require a combined rank below 100 for both liquidity factors. For each share, the excess geometric return is calculated semi-annually at time *t*, while lagged values of size, value, momentum, liquidity, idiosyncratic risk, market beta and currency risk are estimated six months prior at time *t-6*. Return and factor data are then stacked where the individual share (*i*) is required to have at least three periods (18 months) of dependent return data (*t*) and *ex-ante* factor data (*t-1*). The result is a data set with panel properties portraying a cross-section of shares, with each individual share having seven explanatory cross-sectional data points related to independent regressors variables assumed to drive share returns on the JSE, measured over 37 points in time.

The implication is therefore that if a share remains in the liquid universe throughout the sample period, the share will have 296 data points (8 cross-sectional data points including the dependent variable measured over 37 semi-annual periods). Importantly, the nature of liquidity and shares listing and delisting through time implies that shares will blink in and out of the universe resulting in an unbalanced panel. In order to not bias the test, a minimum filter is applied where shares require at least 18 months of (non-continuous) data, implying cross-sectional data over three time periods. The final cross-section of shares after adjusting for liquidity is equal to 241 (N) over the entire sample period, while the number of time series points is equal to a maximum of 37 (T). Since N>T, the panel can be described as ‘short and wide’ per Kennedy (2003) as the cross-section is significantly larger than the time-series component.

The panel is structured to allow for the determination of causality between the individual share returns and the explanatory factors, as each of the independent variables are considered *ex-ante* and are lagged six months. Cochrane (2001) found that the empirical difference between lagged and contemporaneous factors is minimal, however, for the purposes of this study, the lagging of the independent variables is core to the determination of the causal link between stylistic factors and their effect on the cross-sectional variation in share returns. Even though each of the independent variables applied in the panel as explanatory variables have already

been described at length in Chapters Four and Five, the table that follows summarizes each of the variables in terms of their underlying assumptions and estimation.

Explanatory Variable	Estimation (lagged 6 months)
Size	Natural log of market capitalization
Value	Median book-to-market ratio measured over the previous 12 months
Liquidity	Average monthly turnover ratio measured over the previous 12 months
Momentum	Historical cumulative momentum estimated over the previous six minus one months
Idiosyncratic risk	Univariate idiosyncratic risk measured via orthogonalization on the J203 ALSI over the previous 36 months
Market Beta	Liquidity adjusted beta measured assuming a 36 month historical window period using the J203 ALSI as the market proxy
ZAR Beta	Currency risk measured against log normally distributed changes in the ZAR/USD exchange rate over the previous 36 month window period

Table 6.1: Description of independent explanatory variables applied in cross-sectional panel data regressions

A benefit of the panel nature of the data is the econometric models available to determine the effects, causal links, heterogeneity and significant drivers of share returns on the cross-section of shares listed on the JSE. Prior to discussing the results of the panel regressions, the various econometric models and their assumptions are to be discussed in detail, specifically relating the benefits of the said model and application to the current data. The models to be considered are pooled least squares, the fixed effects model and the random effects model. Each model is based on a series of assumptions regarding heteroskedasticity, omitted variable bias and heterogeneity over both individual shares and time.

6.3. POOLED LEAST SQUARES

The pooled least squares model simply 'pools' the data of individuals (shares) without considering potential differences across individuals or time that may bias coefficient estimates. In application to the panel data set described above, the model takes the mathematical form

$$R_{it} = \alpha + \sum \beta_Y X_{Yit} + \varepsilon_{it} \qquad (6.1)$$

Where R_{it} represents the return on share i at time t, α is the intercept calculated and applicable to all shares in the sample (N), β_Y represents a vector of coefficients on Y explanatory

variables, X_{Yit} represents the matrix of explanatory variables for each share i at time t and ε_{it} represents the error term of the regression. Importantly, the model specifically excludes *i* from the parameters α and β_Y as the pooled OLS methodology assumes that both the alpha and beta coefficients are consistent and fixed across individual shares and time.

The panel structure of the data generally precludes the assumptions around the error term generally applied in conventional OLS estimation. Heteroskedasticity and serial correlation are common in panel data sets as individual errors are expected to be correlated across time. An example of this would be an industry effect that is captured in the error term. If the said industry is currently experiencing a bull period, the effect on R_{it} will be similar over a period of time, implying serial correlation as well as heteroskedasticity present in the error structure as the industry effect may be highly correlated with momentum. An essential prerequisite when estimating the pooled OLS model is the application of panel consistent standard errors (PCSE), a similar adjustment to Newey-West consistent standard errors that accounts for variations in the error variance across time but is consistent across individuals. Cochrane (2001) proves that the Fama and Macbeth (1987) two-pass regression procedure is effectively identical to a pooled OLS methodology that corrects for serial correlation in the error structure.

6.4. THE FIXED EFFECTS MODEL

A potential drawback of the pooled least squares model (assuming PCSE) is that it relaxes the OLS assumptions related to the covariance structure of the error term in order to account for heterogeneity within the cross-section of individual shares and across time. By not openly allowing for the implicit heterogeneity, coefficient estimates may be biased as the pooled OLS model assumes that the estimated coefficients are static across individuals and time. The fixed effects model corrects the short-comings of the pooled OLS specification by accounting for heterogeneity in the intercept term, thereby freeing the estimated coefficients from potential confounding issues such as omitted variable bias, serial correlation and (obviously) heterogeneity. A simple example could be that within the cross-section of firm data described above, a single firm produces returns that are contrary to the stylistic results seen in literature i.e. the said share is high beta, low B/M ratio, illiquid and high idiosyncratic risk but achieves high average returns due to an omitted variable such as superior management. The fixed effects model accounts for this heterogeneous effect by allowing the intercept to capture the cross-sectional heterogeneity of the omitted variable, thereby removing the effects from the current set of explanatory variables, resulting in unbiased estimated coefficients. The fixed effects model is expressed mathematically as

$$R_{it} = \alpha_i + \sum \beta_Y X_{Yit} + \varepsilon_{it} \qquad (6.2)$$

The subtle yet fairly obvious difference between the fixed effects model and pooled OLS specification relate to the intercept value α_i whereby the model assumes that the intercept or alpha of share *i* can vary across individuals and time. The assumption does not extend to the estimated coefficients β_Y which are expected to be constant across individuals and time. In order to reiterate the benefit of such a model, a further simple example would be the poor performance of momentum shares in significant market downturns. Since the poor performance of momentum is only in specific periods across the sample, such heterogeneity would be captured in the intercept term, effectively extracting the cyclical effect and removing potential bias from the estimated momentum coefficient. The obvious expected result and benefit of applying the fixed effects model, specifically when encountering cross-sectional or time based heterogeneity, is that the standard errors of the regression parameters will be more accurate and precise, resulting in more efficient coefficient estimates compared to those produced via the pooled OLS specification.

6.5. THE RANDOM EFFECTS MODEL

The description of the fixed effects model presented above indicates that individual differences across shares (heterogeneity) is captured in the intercept parameter α_i. Unlike the fixed effects model, the random effects model assumes that the individual differences across shares are in fact 'random' implying that the intercept term has two components, one fixed and one random, as opposed to being wholly representative of the individual *i*'s heterogeneity. The new specification of the intercept is described mathematically as follows

$$\alpha_i = \bar{\alpha} + \delta_i \qquad (6.3)$$

Where α_i is made up of the population average intercept $\bar{\alpha}$ and random differences across individuals δ_i. The random term is referred to as the 'random' effect and maintains properties similar to that of a typical error term as it is expected to have a zero mean, uncorrelated across individuals and maintains a constant variance (practically identical assumptions to the panel consistent standard errors). The random effects model can therefore be extended from the fixed effects model via

$$R_{it} = \alpha_i + \sum \beta_Y X_{Yit} + \varepsilon_{it} \qquad (6.4)$$

$$R_{it} = (\bar{\alpha} + \delta_i) + \sum \beta_Y X_{Yit} + \varepsilon_{it} \qquad (6.5)$$

$$R_{it} = \bar{\alpha} + \sum \beta_Y X_{Yit} + (\varepsilon_{it} + \delta_i) \qquad (6.6)$$

$$R_{it} = \bar{\alpha} + \sum \beta_Y X_{Yit} + \vartheta_{it} \qquad (6.7)$$

Where ϑ_{it} represents the combined error term that considers both conventional random errors and random effects across individuals. The significant benefit of the random effects model relates to the treatment of in-sample individual cross-sectional differences as random. Relating this to the previous example of a momentum winner share that achieves a negative return over the assumed holding period. A possible cause of the poor performance may be attributable to poor management decisions made in the latter half of the holding period and therefore an omitted variable. The random effects model now allows for momentum shares to maintain a high average alpha $\bar{\alpha}$ and attributes deviations i.e. poor management from alpha as random. The result is that the omitted variable bias and resulting heterogeneity is captured in the random error term δ_i, resulting in unbiased and efficient parameter estimation. Importantly, a key assumption of the random effects model is that the term ϑ_{it} does not display heteroskedasticity. Typical heteroskedasticity implies the error term being correlated with any of the explanatory variables within the matrix X_Y. Similarly, the same requirement is applied to δ_i, however, and similarly, if this assumption is biased, the parameter estimates calculated via the random effects model are both biased and inconsistent.

6.6. WHICH IS THE BEST MODEL?

The question of 'best' is highly dependent on the data. Importantly, a key step in applying the appropriate model would be initially determining whether there are fixed or random effects present in the data set. To test for fixed effects, dummy variables are applied to both the cross-section of individuals and periods, also referred to as 'least squares dummy variable estimators'. The coefficients of the dummy variables (both cross-sectional and time period) are then jointly tested in order to determine whether the fixed effects are redundant. Two tests can be used, namely an F-Test (right-tailed) and a Chi-squared test, where both have a null of "no fixed effects". Failing to reject the null implies that a restricted model that considers a single intercept is appropriate (α and not α_i), implying that there is no heterogeneity, no individual or time differences and thereby indicating that the pooled least squares estimation will produce efficient and unbiased coefficients. One can also test for random effects, where one is effectively testing whether δ_i (specifically the variance of δ_i) is equal to zero. If var(δ_i) is equal to zero, then δ_i is a degenerate random variable implying that it is constant and equal to zero. The result would therefore dictate that there are no random individual differences across individuals and time, implying no random individual heterogeneity, indicating no

random effects. A Lagrange multiplier (LM) test can be applied (potential tests vary with many options such as Breusch and Pagan (1980), Honda (1985), King and Wu (1997)) where the null hypothesis of var(δ_i) equaling zero is tested against the alternative right-sided test of var(δ_i) being greater than zero. If one fails to reject the null, the random effects estimator reduces to

$$R_{it} = \bar{\alpha} + \sum \beta_Y X_{Yit} + \varepsilon_{it} \qquad (6.8)$$

Which is effectively identical to the pooled least squares model and is therefore estimated best using ordinary least squares.

Importantly, if both fixed and random effects are present, Hill, Griffins and Lim (2008) state that the random effects model is superior. Firstly, the random effects model is estimated using generalized least squares (GLS) while the fixed effects model is estimated using OLS. The GLS specification is considered to be superior in large sample scenarios as it produces a lower variance and therefore smaller, unbiased and more efficient coefficient estimates. Secondly, and more importantly, the random effects model takes into account the random sampling applied in collecting data when modeling heterogeneity within the error structure. A major drawback of the random effects model relates to the violation of the assumption relating to heteroskedasticity between δ_i and the independent variables. Relating the issue to an example pertinent to the sample applied within the chapter, consider once again 'superior management' as an omitted variable that under the random effects specification would be confined to the individual shares specific 'random' error component (heterogeneous difference) δ_i. The superior management of the company (in this case δ_i) could very easily be highly correlated with the explanatory variables like momentum, low beta or low idiosyncratic risk (components of X_Y). In such a scenario, the random effects estimator is biased, however, the fixed effects estimator is consistent, even in the face of endogenous regressors and heteroskedasticity between δ_i and X_Y.

The Hausman test, developed by Hausman (1978), effectively tests whether the random effects term δ_i is correlated with the right hand side explanatory variables by comparing the coefficients estimated by both the fixed and random effects models. The Hausman test is based on the logic of both the random and fixed effect coefficient estimates being consistent if δ_i is not correlated with the explanatory variables. Simply, both sets of estimates should converge on true parameter values β_Y in large samples and therefore be similar. Their similarity, however, is contingent on the random effects term not being correlated with the independent explanatory variables. The Hausman test is generally applied as a joint test

(using either an F-test or Chi-squared test) against a set of coefficients estimated assuming both a random and fixed effects model. The null of the Hausman test is that there is no difference between the fixed and random effects, implying that δ_i is not correlated with X_Y and therefore, the random effects model should be used as it is superior to fixed effects model in large samples.

In the sections that follow, each of the three econometric specifications are to be applied in determining the cross-sectional drivers of share returns. Further tests will be conducted in order to determine whether fixed and random effects are present in the data and lastly, which is the most appropriate model and therefore, which parameter estimates are most consistent and efficient. For each specification applied, five regressions are run that take the mathematical form:

$$R_p = \alpha_p + \beta_{p,s}Size + \beta_{p,v}Value + \varepsilon_p \quad (6.9)$$

$$R_p = \alpha_p + \beta_{p,s}Size + \beta_{p,v}Value + \beta_{p,m}Momentum + \varepsilon_p \quad (6.10)$$

$$R_p = \alpha_p + \beta_{p,s}Size + \beta_{p,v}Value + \beta_{p,m}Momentum + \beta_{p,l}Liquidity + \varepsilon_p \quad (6.11)$$

$$R_p = \alpha_p + \beta_{p,beta}MarketBeta + \beta_{p,idio}IDIO + \beta_{p,CR}ZarBeta + \varepsilon_p \quad (6.12)$$

And lastly;

$$R_p = \alpha_p + \beta_{p,s}Size + \beta_{p,v}Value + \beta_{p,m}Momenttum + \beta_{p,l}Liquidity + \beta_{p,beta}MarketBeta + \beta_{p,idio}IDIO + \beta_{p,CR}ZarBeta + \varepsilon_p \quad (6.13)$$

The subscript *p* in the above specifications refers to the panel nature of the data, purposefully not specifying the applicable model but rather allowing for the application of the pooled OLS, fixed effects and random effects models to be applied. Each of the regressions to be estimated contain a varying combination of the factors described in Table 6.1. The pen-ultimate regression (Equation 6.13) considers all of the considered factors and therefore should provide insight into the key drivers of cross-sectional variation in share returns on the JSE. Paramount to this study is whether momentum maintains a significant coefficient and positive sign irrespective of specification. Such a result would indicate that momentum does significantly contribute to cross-sectional variation in share returns, is priced on the JSE and therefore requires (and deserves!) inclusion within an asset pricing model that describes the risk – expected return relationship on the JSE.

The following sections will consider the regression results for each of the econometric specifications applied, where results will be discussed in terms of the coefficient values, economic magnitude and statistical significance and further related to the results presented in Chapters Four and Five of this study as well as international and local literature.

6.6.1. Empirical Results – Pooled Ordinary Least squares

The results of the pooled OLS specification are presented in Table 6.2. The table depicts the coefficient parameters of the explanatory independent variables applied in regressions one to five, with the regression number depicted in the first column on the left. The emboldened and italicized p-value of each coefficient is presented below the respective coefficient. Lastly, the adjusted R^2 values are displayed in the far right column. As described previously, each regression is run assuming panel consistent standard errors (PCSE) in order to correct parameter standard errors for potential heterogeneity across individual shares within the panel. Regression I considers value, proxied by the book-to-market ratio and size by the natural log of market capitalization. As mentioned, both variables are lagged in order to determine the causal link between *ex-ante* price factors and *ex-post* share returns. Regression I is effectively testing the Fama and French (1992, 1995 and 1996) factors. Consistent with the findings of Fama and French (1992), van Rensburg and Robertson (2003), Auret and Sinclaire (2006), Basiewicz and Auret (2009), Gilbert, Strugnell and Kruger (2011) and Page and Auret (2013), both size and value seem to be significant determinants of the future cross-sectional variation in share returns listed on the JSE over the period January 1997 to June 2015.

The value coefficient is positive and significant at the 1% level while similarly the size coefficient is negative and significant at the 1% level. The coefficient values indicate that a single unit positive change in the lagged book-to-market ratio of a share will result in a positive holding period monthly average return of 0.3%. Conversely, a one unit positive change in the size of a company would result in a negative -0.23% change in the expected average return. The adjusted R^2 of the regression indicates that size and value alone only seem to explain 0.89% of the total variation in share returns over the sample period. Regression II considers the Fama-French factors but extends the analysis to include the historical six minus one month momentum, effectively representing a test of the Carhart (1997) four factor model. Firstly, momentum seems to add significant explanatory power as the adjusted R^2 has increased from 0.89% to 1.27%, representing a 41% increase in explanatory power.

Regression	β_{Value}	β_{Size}	$\beta_{Momentum}$	$\beta_{Liquidity}$	$\beta_{Market\ Beta}$	$\beta_{Idiosyncratic\ risk}$	$\beta_{Currency\ Beta}$	Adj. R2
I	0.0030	-0.0023						0.89%
	0.0005*	***0.0000****						
II	0.0030	-0.0022	0.0116					1.27%
	0.0005*	***0.0000****	***0.0016****					
III	0.0029	-0.0028	0.0116	0.0009				1.33%
	0.0008*	***0.0000****	***0.0016****	***0.0762****				
IV					-0.0130	0.0145	0.0023	1.83%
					0.0000*	***0.5116***	***0.0628****	
V	0.0028	-0.0029	0.0091	0.0014	-0.0101	-0.0282	0.0024	2.80%
	0.0014*	***0.0000****	***0.0127***	***0.0080****	***0.0000****	***0.2648***	***0.0549****	

*Table 6.2: Pooled OLS regression estimates utilizing value, size, momentum, liquidity, liquidity adjusted market beta, idiosyncratic risk and currency risk over the sample period January 1997 to June 2015. All regressions are run assuming panel consistent standard error (PCSE) in order to account for the potential in-sample heterogeneity and serial correlations across time for individual shares within the panel. P-values are emboldened and assigned asterisks where *, **, *** indicates significance at the 10%, 5% and 1% level.*

The coefficients for size and value are largely unchanged with both still remaining significant at the 1% level and retaining their correct signs. As expected, the momentum factor is positive and significant at the 1% level. Importantly, the economic size of the momentum coefficient is four and five times greater than the value and size coefficients respectively. Relating the results to returns, the momentum coefficient indicates that a one unit increase in historical momentum measured over the previous six minus one months will result in an additional 1.2% in average return per month. The results are therefore consistent with the findings of Jegadeesh and Titman (1993, 2001), Fraser and Page (2000), Carhart (1997), van Rensburg (2001), Hodnett, Hsieh and van Rensburg (2012), Muller and Ward (2013) and Page, Britten and Auret (2016) all of whom found that momentum is a priced and significant factor on the global and local cross-section of listed equities.

Regression III simply augments the Carhart (1997) model to include a liquidity factor proxied by ex-ante turnover measured over the previous 12 months. Interestingly, the inclusion of the liquidity proxy results in the size coefficient becoming more negative, decreasing further to -0.0028, while having little to no effect on the value and momentum coefficients. The liquidity coefficient itself is inconsistent with findings Amihud and Mendelson (1986), Pastor and Stambaugh (2003) and more recently Ibbotson, Chen, Kim and Hu (2013) as there is no indication of the typical liquidity premium espoused in literature. The findings are however consistent with Rouwenhorst (1999) who found that the liquidity premium was virtually non-existent in emerging markets. The '*a priori*' expectation implies that low liquidity shares should produce higher returns than high liquidity shares in order to compensate investors for bearing additional liquidity risk. The result however indicates the opposite, as expected share returns on the JSE seem to increase given a higher level of univariate liquidity. There are a number of potential reasons behind the result.

Firstly, the investable universe is limited to the top 100 shares based on market capitalization and value traded, implying that the universe is relatively more liquid than an unconstrained universe. The result is an immediate bias against finding a liquidity premium as there is a limitation on truly illiquid shares. A second possible and highly plausible reason could be the proxy used for liquidity. To the best of the author's knowledge, there is limited literature related to the optimal liquidity proxy on the JSE and is certainly an avenue of future research. Irrespective of the incongruent result, the liquidity coefficient is positive and significant at the 10% level and indicates that a single unit increase in ex-ante liquidity (proxied by turnover) will result in 0.09% increase in monthly average return and are therefore consistent with the results expressed in Chapter Five. Importantly, the original Carhart (1997) factors are largely insensitive to the incorporation of liquidity in the regression specification.

Regression IV considers the 'regressed' factors, namely; liquidity adjusted beta, idiosyncratic risk orthogonalised on the J203 ALSI and currency beta measured against monthly changes in the ZAR/USD exchange rate. Per the findings of van Rensburg and Robertson (2003), Baker, Bradley and Wurgler (2011) and Frazzini and Pedersen (2014), the ex-ante liquidity adjusted beta coefficient is negative and significant at the 1% level, indicating that the low beta anomaly is present and significant (at the 1% level) on the JSE. The coefficient indicates that a one-unit increase in ex-ante market beta results in a 1.3% decrease in average return over the following period. The results for both idiosyncratic risk and currency beta are less convincing. The idiosyncratic risk coefficient indicates that returns maintain a statistically insignificant positive relationship with *ex-ante* idiosyncratic risk. The result is therefore inconsistent with the notion of a low volatility premium as expressed by Malkiel and Xu (2006), Ang, Hodrick, Xing and Zhang (2009) and Baker, Bradley and Wurgler (2011).

Similarly, the currency beta coefficient is inconsistent with the recent findings of Page, Britten and Auret (2015) as the coefficient is positive and significant at the 10% level. The results of Page, Britten and Auret (2015) dictate that rand tracker shares or shares with historically low or negative currency betas achieve significant excess returns over their rand hedge counterparts. The regression results indicate the inverse, as the currency beta coefficient is both positive and significant, depicting that a one unit increase in currency beta is expected to produce an additional 0.2% return per month on average. Importantly, the regressed factors do seem to contain a large amount of explanatory power in terms of the cross-sectional variation in share returns as the three factors alone produce an adjusted R^2 of 1.83%, explaining effectively 5% more (on a relative basis) than the augmented Carhart (1997) (Regression III) specification.

The fifth and final regression estimated using pooled least squares indicates that six of the seven factors considered remain significant and consistent in terms of sign and magnitude. Both size and value retain their signs, indicating that the *ex-ante* book-to-market ratio and natural logarithm of market capitalization maintain the expected positive and negative relationships with expected return. The value coefficient indicates that a one-unit increase in the book-to-market ratio of a share will result in 0.28% increase in the expected average monthly return and the effect is significant at the 1% level. Similarly, the size coefficient indicates that a one unit increase in the natural logarithm of market capitalization will result in reducing the expected average monthly return of a share by -0.28% per month and is also significant at the 1% level. The inclusion of the regressed factors within the regression results in a marginal economic decrease in the momentum coefficient, reducing to 0.91% per month, and just misses significance at the 1% level.

The liquidity premium drops significantly in the final regression, however the relationship displayed is still positive and significant at the 1%, implying that shares returns seem to maintain a positive relationship with liquidity (when proxied by the turnover ratio). The low beta effect seems to present and significant on the JSE, as liquidity adjusted beta maintains a significantly negative relationship with expected monthly share returns. The liquidity adjusted beta coefficient entails that a one-unit increase in market beta results in a 1.01% decrease in expected monthly returns and is significant at the 1% level. Like the results of Regression IV, the coefficient estimates for idiosyncratic risk and currency beta are inconsistent with evidence presented in literature.

The idiosyncratic risk coefficient now portrays the correct sign and is economically large but lacks statistical significance. Similarly, the coefficient of the currency risk factor is relatively unchanged and significant at the 10% level, yet the sign of the coefficient is inconsistent with the recent findings of Page, Britten and Auret (2015) as the expected relationship between expected returns and currency risk is inverse, yet a positive coefficient implies that an increase in currency beta i.e. movement towards rand hedge qualities, implies greater future average returns. Lastly, it should be noted that the inclusion of all factors results in the highest adjusted R^2 of 2.8%, implying that the explanatory variables considered explain the highest proportion of variability in share returns when considered simultaneously. It should be further noted that the usage of a share-by-share aggregation should result in relatively low R^2 as one would anticipate a high level of noise in time-series and cross-sectional returns.

6.6.2. Empirical Results – Fixed Effects Model

As described in Section 6.4 above, the fixed effects model assumes that coefficient parameter estimates are fixed across individual shares and time while all heterogeneous differences are captured in the intercept term. Prior to running the fixed effects model, it is imperative to determine whether there are cross-sectional or time-series fixed effects present within the data. Appendix 2a depicts the redundant fixed effects test that utilizes a likelihood ratio test using both an F-distribution and Chi-squared distribution. The null hypothesis is that the data does not display cross-sectional or time-series fixed effects. Both tests, using the F-distribution and Chi-squared, reject the null hypothesis in favor of the alternate hypothesis at the 1% level, implying that the data displays significant heterogeneity across time and individuals. The fixed effects model is therefore run assuming fixed effects present across individual shares and time. The results of the fixed effects estimation are displayed in the table that follows. Under the assumption of the fixed effects model, five regressions are run using the identical variable specifications as those presented in Table 6.2. Importantly, the fixed effects model is

estimated using ordinary lease squares, therefore all regressions are again run assuming panel consistent standard errors (PCSE).

The first regression depicts the results only considering size and value as explanatory factors. The value coefficient is economically identical to pooled least squares estimate, indicating that a one unit increase in the lagged book-to-market ratio results in a 0.28% increase in expected average monthly return and just makes significance at the 5% level. Conversely, the application of the fixed effects model seems to have a major impact on the size coefficient. The size coefficient now indicates that a one unit increase in the natural log of market capitalization results in a decrease in expected average return of 1.8% per month and is significant at the 1% level, implying a 9.1 times increase when compared to its pooled least squares counterpart. Regression I further produces an adjusted R^2 of 27.8% which is significantly higher than that of the pooled least squares model. Higher R^2's are expected as heterogeneity is modeled using cross-sectional and time-series dummy variables, which should inevitably result in higher R^2 estimates due to more explanatory variables. The results of Regression II are highly similar to those of Regression I, as both value and size maintain coefficients of identical sign and magnitude.

The momentum coefficient is positive and significant at the 1% level. The application of the fixed effects model has no material impact on the momentum coefficient as it is effectively identical to its pooled least squares estimate. The coefficient indicates that a one-unit increase in historical momentum results in a 1.21% increase in expected average monthly return. Further, inclusion of momentum increases the adjusted R^2 to 28.11%, effectively adding an additional 0.32% explanatory power to the specification. Regression III augments the previous regression by adding liquidity, proxied by turnover, as an explanatory variable. Interestingly, the sign of the liquidity coefficient is now consistent with the findings of Amihud and Mendelson (1986), Pastor and Stambaugh (2003) and more recently Ibbotson, Chen, Kim and Hu (2013) and inconsistent with Rouwenhorst (1999) and Page, Britten and Auret (2013) as it is both negative and significant. The coefficient implies that a one unit increase in the lagged turnover ratio results in a decrease in expected average monthly return of -0.22% and is significant at the 5% level. Further, the inclusion of liquidity does not seem to detract from the size or momentum coefficients and actually seems to have a positive effect on the value coefficient, which increases to 0.296 and is more convincingly significant at the 5% level.

As mentioned previously, Regression IV considers the 'regressed' factors/premiums that have been applied within the study. The results are highly similar to those of the pooled least squares estimates as the liquidity adjusted market beta coefficient is in-line with international literature, however the results are less convincing for idiosyncratic and currency risk. The

liquidity adjusted beta coefficient is negative and highly significant, implying a robust and consistent low-beta effect present on the JSE. The coefficient indicates that a one unit increase in the lagged liquidity adjusted beta will result in a decrease in expected average monthly return of -1.23% and is significant at the 1% level. Unfortunately, the idiosyncratic risk coefficient is significant but the wrong sign, indicating that an increase in lagged idiosyncratic risk results in a positive increase in expected monthly average returns, consistent with Markowitz (1953). The currency beta coefficient is now the correct sign and therefore consistent with the findings of Page, Britten and Auret (2015), depicting a negative relationship between currency beta and expected returns. Unfortunately, the correctness of the sign is limited by the fact that the coefficient is not significantly different from zero.

The final regression considers all of the explanatory variables simultaneously. Five of the seven coefficients are significant with the parameters not changing significantly when compared to Regressions I to IV. Both size and liquidity seem to be more consistent when estimated assuming cross-sectional and time period fixed effects. The size coefficient does not drop below -1.6% across the various regressions and the liquidity coefficient maintains a negative sign, implying consistency with the globally accepted liquidity premium. The value, momentum and market beta coefficients are largely consistent with the pooled least squares parameter estimates and maintain significance at the 1% level. Unfortunately, the fixed effects model indicates that neither currency risk nor idiosyncratic risk are significant determinants of future cross-sectional variation in share returns.

Regression	β_{Value}	β_{Size}	$\beta_{Momentum}$	$\beta_{Liquidity}$	$\beta_{Market\ Beta}$	$\beta_{Idiosyncratic\ risk}$	$\beta_{Currency\ Beta}$	Adj. R^2
I	0.0028	-0.0182						27.79%
	0.0451	***0.0000****						
II	0.0028	-0.0175	0.0121					28.11%
	0.0490	***0.0000****	***0.0013****					
III	0.0030	-0.0168	0.0117	-0.0022				28.20%
	0.0350	***0.0000****	***0.0018****	***0.0400****				
IV					-0.0123	0.1073	-0.0024	24.50%
					0.0000*	***0.0008****	***0.1908***	
V	0.0030	-0.0163	0.0102	-0.0019	-0.0075	0.0219	-0.0016	28.43%
	0.0326	***0.0000****	***0.0071****	***0.0843****	***0.0018****	***0.5012***	***0.3811***	

*Table 6.3: Fixed Effects (Cross-sectional and Time-series) regression estimates utilizing value, size, momentum, liquidity, liquidity adjusted market beta, idiosyncratic risk and currency risk over the sample period January 1997 to June 2015. As the Fixed Effects model is estimated using Ordinary Least Squares, each regression is run assuming panel consistent standard error (PCSE) in order to correct for the potential in-sample heterogeneity and serial correlations across time for individual shares within the panel that may still bias standard errors. P-values are emboldened and assigned asterisks where *, **, *** indicates significance at the 10%, 5% and 1% level.*

The results of the final regression indicate that value, size, momentum, low beta and to lesser extent, liquidity, are significant and consistent determinants of future share returns on the JSE. The fixed effects model seems more appropriate to the data as it allows for firm level and time-period heterogeneity to be captured in the intercept term and not cloud the regression parameters. Logically, one can expect that there is most certainly a time and individual based level of heterogeneity present on the JSE. In terms of time-based heterogeneity, it is definitely possible that certain priced factors do not perform well over certain periods. An example of this would be that over certain periods growth may outperform value or momentum shares are punished during a bear market cycle. Cross-sectional based heterogeneity is even easier to contemplate.

Consider the share Naspers (share code NPN), which is considered a mega capitalization share. This mega-sized share, which has been considered a mega—size share over the last two years, has produced brilliant returns, appreciating over 50% in the most current year and 270% over the last three years. The main cause of the meteoric ascension relates to Naspers 34% investment in the Chinese online shopping and logistics company Tencent. Considering only the size effect, such information would be an omitted variable and hence contribute to heterogeneous differences between Naspers and other large capitalization companies, which are expected to perform poorly. Therefore, since there are both time and individual effects (as seen through the redundant fixed effects tests) across the data, the parameter estimates garnered through the application of the fixed effects model seem more appropriate and applicable than those estimated via the pooled OLS specification.

6.6.3. Empirical Results – Random Effects Model

As discussed previously, the random effects model is similar to the fixed effects model in that it also accounts for heterogeneity in the intercept term. However, the heterogeneous effects are considered to be random across individuals and time and can therefore be incorporated within the error term. Therefore, the error term is now augmented by δ_i, representing the heterogeneous random effects across individuals and time. Like the fixed effects model, one can test for random effects where the nature of the test considers the variation in δ_i. Discussed above, the basic principles of the conventional OLS error term apply to the random effect δ_i, where the expectation is zero but the variance is non-zero. If the variance is zero, then the random effect is a degenerate random variable and effectively constant and would imply that the pooled least squares estimator is both sufficient, consistent and the most appropriate specification. Appendix 2b displays the results of the random effects tests. The tests indicate that the cross-sectional random effects variance is not significantly different from zero,

however, the time-period random effects maintains a non-zero variance. Such a result is intuitively appealing, as it is highly consistent with asset pricing theory and factor premiums driving returns.

The purpose of asset pricing theory and asset pricing models is to define a set of factors that successfully explain the cross-sectional variation in share returns and therefore transcend firm specific effects or cross-sectional heterogeneity. Unfortunately, it is expected that such premia cannot be perfectly consistent throughout all market conditions. The implication therefore is that factors drive cross-sectional variation in share returns yet, the factors themselves may not and generally are not always consistent through time. Consider the financial and liquidity crisis over 2008/2009. Momentum, which has maintained phenomenal returns prior and post the period-experienced significant drawdowns in excess of 20% over a three-month period. The figure below indicates the extreme changes experience over the time frame.

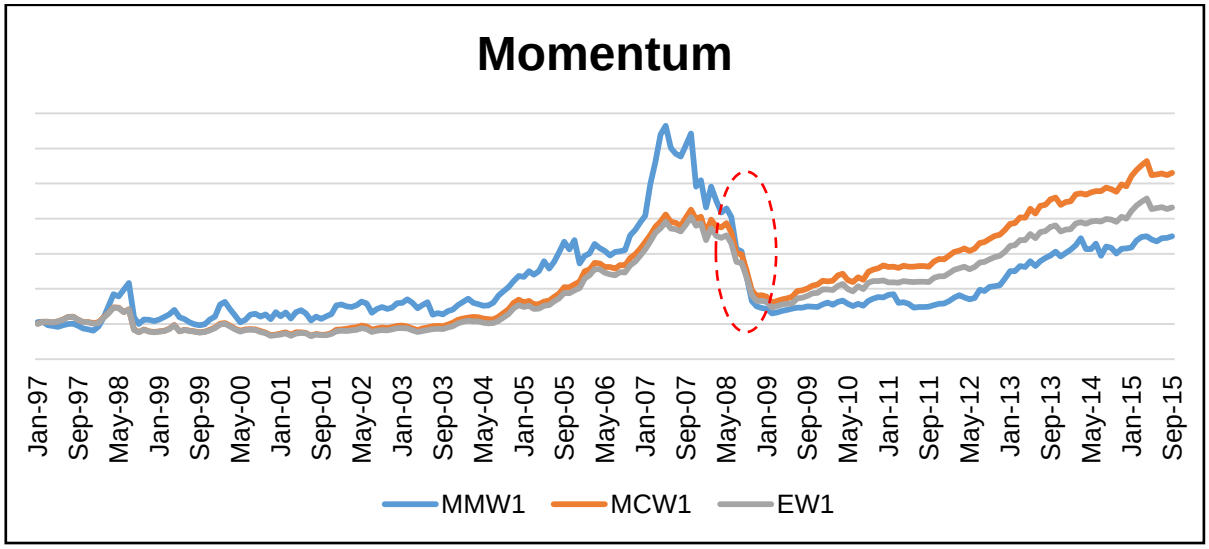


Figure 6.1: Momentum cumulative returns over the period January 1997 to June 2015. MMW1 represents the momentum weighted winner portfolio, MCW1 represents the market capitalization weighted winner portfolio and EW1 represents the equally weighted winner portfolio. The red dotted circle depicts the period of significant drawdowns over the 2008/2009 financial and liquidity crisis

The figure indicates both the meteoric rise and fall of momentum over the sample period considered. The results of the random effects indicate that, as expected, factor premiums can vary through time but are not impervious to exogenous market wide shocks and can possibly underperform other factors or the market itself. The results of the random effects tests are therefore consistent with general asset pricing theory in allowing for heterogeneous deviations through time. The random effects regressions are therefore run assuming time period random effects and not cross-sectional random effects. The regression results are displayed in Table

6.4 that follows. Akin to the results of the pooled OLS and fixed effects estimates, Regression I indicates that size and value (proxied by the book-to-market ratio) are significant cross-sectional determinants of share returns on the JSE. Unlike the fixed effects estimator, the random effects coefficient estimates for size and value are economically similar, indicating that a one unit increase (decrease) in the book-to-market ratio (natural log of market capitalization) will result in a 0.24% (0.18%) increase in average expected monthly return.

Regression II presents the Carhart (1997) specification. Both size and value maintain their significance and the correct sign, however, the random effects parameter estimate for momentum is economically higher than those achieved by the fixed effects and pooled OLS estimates. Firstly, as expected, the momentum coefficient is significant and positive, yet the coefficient indicates that a one unit increase in the historical six minus one cumulative return results in an increase of 2.25% in expected average monthly return. A basic comparison indicates that the random effects momentum coefficient implies 1.09% and 1.04% more average expected monthly return when compared to the parameter estimates of the pooled OLS and fixed effects estimates respectively. Regression III augments the model to include liquidity proxied by turnover. Consistent with the pooled OLS specification and therefore inconsistent with international literature and the fixed effects model, the liquidity coefficient is positive and not significantly different from zero. Furthermore, the incorporation of liquidity seems to have a minimal effect on size, value and momentum, with each of the explanatory variables maintaining their signs, significance and economic magnitude.

Regression IV considers the ‘regressed’ factors, namely liquidity adjusted beta, idiosyncratic risk and currency beta. As expected and consistent with the pooled OLS and fixed effects regressions, *ex-ante* liquidity adjusted beta produces a significantly negative coefficient, indicating that the low beta premium is present on the JSE. The coefficient predicts that a one-unit increase in liquidity-adjusted beta will result in a decrease in expected average monthly return of 0.93%. Unique to the random effects model, the sign of the idiosyncratic risk coefficient is consistent with international literature on the low volatility premium, indicating that a one unit increase in idiosyncratic risk will result in a decrease in expected average monthly return of -0.62%. Unfortunately, the idiosyncratic risk coefficient is statistically insignificant even though it is economically larger that the size and value coefficients in regressions I to III.

Regression	β_{Value}	β_{Size}	$\beta_{Momentum}$	$\beta_{Liquidity}$	$\beta_{Market\ Beta}$	$\beta_{Idiosyncratic\ risk}$	$\beta_{Currency\ Beta}$	Adj. R^2
I	0.0024	-0.0018						0.60%
	0.0023*	***0.0001****						
II	0.0023	-0.0016	0.0225					2.09%
	0.0032*	***0.0006****	***0.0000****					
III	0.0023	-0.0018	0.0225	0.0003				2.07%
	0.0036*	***0.0013****	***0.0000****	***0.5449***				
IV					-0.0093	-0.0062	-0.0021	1.12%
					0.0000*	***0.7003***	***0.0569****	
V	0.0026	-0.0016	0.0218	0.0005	-0.0064	-0.0398	-0.0020	2.90%
	0.0012*	***0.0083****	***0.0000****	***0.2496***	***0.0000****	***0.0228*****	***0.0704****	

*Table 6.4: Random Effects (Time-series only) regression estimates utilizing value, size, momentum, liquidity, liquidity adjusted market beta, idiosyncratic risk and currency risk over the sample period January 1997 to June 2015. The Random Effects model is estimated using Generalized Least Squares yet Panel Consistent Standard Errors are still assumed (PCSE). P-values are emboldened and assigned asterisks where *, **, *** indicates significance at the 10%, 5% and 1% level.*

Lastly, the currency risk coefficient is negative and significant at the 10% level. The result is consistent with the findings of Page, Britten and Auret (2015) as they presented evidence in favor of rand tracker shares (shares with cross-sectionally low currency betas) producing higher returns than rand hedge shares. The coefficient indicates that a one-unit increase in currency beta is expected to be met with a 0.21% decrease in expected average monthly return and is significant at the 10% level.

The final regression depicts the results of simultaneously including all of the various factors within a single model specification. The results indicate that when utilizing a time-period random effects model, six of the seven factors considered are significant determinants of returns, five of which are significant at the 5% and 1% level. Both the size and value coefficients remain significant and maintain the correct sign, consistent with the findings of van Rensburg and Robertson (2003), Auret and Sinclaire (2006), Basiewicz and Auret (2009) and Gilbert, Strugnell and Kruger (2011). Interestingly, the value coefficient increases economically in the final regression, implying that a one-unit increase in the lagged book-to-market ratio is met with a 0.26% increase in expected average monthly return. Conversely, the size coefficient decreases marginally, indicating that a one unit increase in the natural log of market capitalization results in a -0.16% decrease in expected average monthly return.

The momentum coefficient decreases marginally, but is still highly significant and economically large, indicating that a one unit increase in historical six minus one month cumulative return results in a 2.2% increase in expected average monthly return. Once again, the liquidity coefficient is inconsistent with the international findings related to the liquidity premium per Amihud and Mendelson (1986). The coefficient indicates that a one-unit increase in the turnover ratio results in an insignificant 0.05% increase in average return. As mentioned previously, the result may be driven by two reasons. Firstly, turnover may be a poor proxy for liquidity on the JSE. Secondly, the sample has been limited to consider a highly liquid universe of South African shares. The plausibility of finding a liquidity premium is limited when eliminating the prospect of investing in truly illiquid shares.

Liquidity adjusted beta achieves a negative coefficient, providing evidence in favor of the low beta premium consistent with the findings of Baker, Bradley and Wurgler (2011) and Frazzini and Pedersen (2014). The liquidity adjusted beta coefficient decreases economically when compared to Regression IV, indicating that a one unit increase in market beta results in a 0.64% decrease in expected average monthly return, but still retains significance at the 1% level. For the first time, the regression results are consistent with the low idiosyncratic risk anomaly, indicating that a one unit increase in volatility translates into a 3.98% decrease in expected returns and is significant at the 5% level. The result is highly consistent with the

findings of Baker, Bradley and Wurgler (2011) as there seems to be a low volatility effect present on the cross-section of shares listed on the JSE that is independent of the low beta effect. The result is also consistent with the bivariate sorts conducted in Chapters Three and Four which presented evidence of a consistent and significant low volatility premium. Lastly, the currency beta coefficient is economically similar to that of Regression IV, implying a 0.2% decrease in average expected monthly return for a given unit increase in currency beta. The coefficient is still significant at the 10% level and therefore consistent with the findings of Page, Britten and Auret (2015), indicating that there is an inverse relationship between currency beta and average return.

In attempt to determine the 'best model' that is most applicable to the current data set, the Hausman test is applied. As discussed, since there are both random and fixed effects present in the data, the pooled OLS is probably not the best specification to use in describing the factors that drive the cross-sectional variation in share returns on the JSE. There are obvious benefits of applying the random effects model. Firstly (and as mentioned previously), the random effects parameters are estimated using generalized least squares and are more efficient as GLS produces a lower variance in large samples. Secondly, the random effects model assumes that cross-sectional or time based heterogeneity is "random" and is therefore better suited to the stochastic nature of share returns (or statistical inference in general).

Obviously the said benefits are offset against the requirements pertaining to δ_i. If the "new" error term of the random effects model is correlated with the right hand side variables used to describe share returns, the coefficients are potentially biased and inconsistent. The issue of "endogenous regressors" is plausible specifically when considering that explanatory variables themselves are random. Referring back to the example of 'good management'. A proactive and dynamic management team is obviously an omitted variable and therefore captured in the error term ϑ_{it}. It is highly possible that good management practices and personnel is highly correlated with any of the independent explanatory variables like momentum, value etc. As discussed in section 6.6, the Hausman test compares the random and fixed effects parameter estimates under the notion that both models should converge on true coefficient estimates in large samples and therefore be highly similar. However, if there is significant levels of correlation between δ_i and the regressors, the random effects estimator will converge on some other value.

Importantly, the potential difference between the estimates may be driven by other reasons such as model misspecification or other explanatory variables that have yet to be defined. Using the random effects model estimated assuming only time-based random effects, the

Hausman test is applied assuming a Chi squared distribution. The results of the Hausman test are displayed in the table that follows.

Test Summary	Chi Squared Test Statistic	Degrees of Freedom	Probability
Period Random	13.6991	7.0000	**0.0568***

*Table 6.5: Hausman Test applied assuming period random effects against the cross-section and period fixed effects estimates. P-values are emboldened and assigned asterisks where *, **, *** indicates significance at the 10%, 5% and 1% level.*

The null hypothesis of the random effects estimator not being biased (I.e. not correlated with the right hand side regressors) is rejected at the 10% level of significance. The result is therefore debatable as the null is rejected, but only at the 90% confidence interval. In application to statistical testing, the ideal would be a 1% level rejection and at minimum a 5% level of significance. As discussed previously, the optimality of the random effects model is undoubtable, however, there does seem to be moderate endogeneity between the random effects error component and the right hand side regressors applied across the regression specifications. *Prima facie,* both the fixed and random effects models seem applicable. The redundant fixed effects tests indicated the presence of both cross-sectional and period fixed effects while the random effects tests found only period random effects, which is easily reconcilable with asset pricing theory. As opposed to defining the optimal model, the results of the three econometric specifications are compared and consolidated in Table 6.6 that follows. The purpose of the consolidation is to determine a finite set of factors that are consistently significant across specifications and can therefore be considered true and unbiased parameters that describe the cross-sectional variation in monthly share returns on the JSE.

A description of the most consistent factors removes the need to determine the most appropriate econometric model as the focus is shifted to defining the best determinants of cross-sectional variation in share returns on the JSE from a set of internationally and locally considered priced factors.

Variable	Pooled OLS	Fixed Effects	Random Effects	Factor Inclusions	Significance Proportion	Relationship Consistent with Literature
Value (B/M)	0.2926%	0.2888%	0.2414%	12.00	100%	100%
Size (market cap)	-0.2531%	-1.7190%	-0.1692%	12.00	100%	100%
Momentum	1.0801%	1.1346%	2.2267%	9.00	100%	100%
Liquidity	0.1137%	-0.2027%	0.0374%	6.00	67%	33%
Liquidity Adj. Beta	-1.0063%	-0.7528%	-0.6419%	6.00	100%	100%
Idiosyncratic Risk	-2.8154%	2.1918%	-3.9800%	6.00	33%	50%
Currency Risk	0.2373%	-0.1581%	-0.2014%	6.00	67%	67%

Table 6.6: Regression results and econometric specification summary

Table 6.6 above describes the average coefficient value per econometric specification, the number of times each factor is included within a regression specification, the percentage of significant coefficients and lastly, the consistency of the coefficient sign with both international and local literature. The benefit of the consolidation and the final two columns of Table 6.6 allows for the determination of the specific stylistic factors that consistently drive the cross-sectional variation in share returns on the JSE, irrespective of the econometric model applied. The first three columns depict the average coefficient per econometric specification where optimal scenario is consistency across the three models.

The value effect is well documented internationally and locally, where shares that trade at a discount to their intrinsic value are considered value shares. The results indicate that there is a consistent independent value premium present on the cross-section of shares listed on the JSE, with the three econometric models producing coefficients between 0.24% and 0.29%. The last three columns indicate that of the twelve inclusions (and therefore twelve value coefficients) all are significant and are of the correct sign, implying a positive relationship between the book-to-market ratio and expected returns, confirming the findings of Fama and French (1993, 1996), van Rensburg and Robertson (2003), Auret and Sinclaire (2006), Basiewicz and Auret (2009) and Gilbert, Strugnell and Kruger (2011). The size results are marginally more varied, with size proxied by market capitalization achieving an economically lower coefficient than value in absolute terms. The largest average size coefficient was

achieved by the fixed effects regression, indicating that a one unit increase in the natural log of market capitalization results in a 1.72% decrease in average monthly return, compared to a 0.25% and 0.17% per the pooled OLS and random effects regressions.

Like value, size was included in twelve of the fifteen regressions, achieving statistical significance and maintaining the correct sign throughout. The result is therefore consistent with the findings of Fama and French (1993, 1996), van Rensburg and Robertson (2003), Auret and Sinclaire (2006), Basiewicz and Auret (2009) and more recently Page and Auret (2014). Interestingly, the result of finding a significant size effect on the JSE is inconsistent with the evidence presented by Auret and Kline (2011), Muller and Ward (2013) and Page Britten and Auret (2016) and even with findings presented in Chapters Four and Five of this study. It is important to note that the sample period considered spans from January 1997 to June 2015. Most findings related to the size effect indicate that beyond the late 2000's, the size effect had largely begun to dissipate. A possible reason for finding a significant size effect could be the time-period considered that contains an initially "strong" size effect that reduces through time. An obvious rectification would be the splitting of the entire sample into two subsamples and comparing the regression results.

A further plausible explanation possibly relates to the 'medium' size effect. The results of the univariate sorts on market capitalization presented in Chapter Five indicate that the larger portfolios produce high levels of return. However, the results presented in the regression analysis above describe a definitive inverse relationship between size and average return. The cross-sectional test applied within this Chapter limits the investable universe of the top 100 shares based on value traded and market capitalization. The obvious result is that there are no micro-capitalization or even small capitalization shares present in the data set rather only large and medium shares. A possible explanation for the negative relationship between size and expected return therefore may be confined to medium and large market capitalization shares outperforming mega-capitalization shares on the JSE over the sample period. The results presented in Chapter Five may be clouded by the fact that the upper portfolios (specifically Portfolios 1-3) contain the medium to mega-sized shares and hence removes the ability to discern between large and medium capitalization shares. The results presented above therefore introduce avenues of further research specifically related to the negative relationship between size and expected returns in the more liquid and larger stratum of shares on the JSE. It should be stressed that the results do not present a size effect where small capitalization shares outperform their large counterparts as the limitations placed on the investable universe exclude typically small and micro-capitalization shares.

The coefficients achieved by the momentum factor, more specifically the historical six minus one-month cumulative return, vary from 1.08% to 2.23% per month on average. As mentioned, the random effects model produces the highest momentum coefficients, indicating that a one unit increase in the historical six minus one month cumulative return results in an increase of 2.23% per month in average expected monthly return. The economic difference between the coefficients is sizeable, with the random effects coefficient being 2.06 and 1.96 times greater than the pooled OLS and fixed effects momentum coefficient estimates respectively. The final three columns of table 6.6 indicate that of the nine scenarios that momentum was included within regressions, all nine were statistically significant and of the correct sign. The results are therefore highly consistent with the findings of Jegadeesh and Titman (1993, 2001), Fama and French (1998), van Rensburg (2001) and more recently Page, Britten and Auret (2013), Muller and Ward (2013) and Page, Britten and Auret (2016).

The results prove that momentum is both independent and highly significant on the cross-section of shares listed on the JSE. In addition, the results also demonstrate that momentum is a significant determinant of the cross-sectional variation in expected returns on the JSE. Liquidity, proxied by turnover, does not seem to be consistently priced on the JSE, with only the fixed effects model presenting a conventional liquidity premium. The final two columns indicate that the liquidity coefficient is only significant in 67% of the regressions estimated while only 33% of the liquidity coefficients present the correct sign, depicting a liquidity premium consistent with the findings of Amihud and Mendelson (1986).

The regressed factors considered as explanatory variables did not fare as well as the more commonly used Carhart (1997) factor premiums. The liquidity adjusted beta coefficient was relatively consistent, achieving coefficients ranging from -0.64% to -1.01% on average. Importantly, the liquidity adjusted market beta coefficient was significantly negative across the regression specifications indicating that the low beta phenomenon is significant and independent on the JSE. The findings are therefore consistent with those of Baker, Bradley and Wurgler (2011) and Frazzini and Pedersen (2014). To the best of the author's knowledge, this is the first documented linear case of the low beta phenomenon explaining share returns on the JSE. Unfortunately, the results are not as positive for the low volatility and currency risk factors. The low volatility coefficient varied significantly across the econometric specifications, ranging from positive 2.19% to minus -3.98%. Of the six inclusions, only two of the coefficients were significant and only one of which was the correct sign.

A possible issue may relate to the methodology applied in defining idiosyncratic risk. The idiosyncratic risk metric applied across this study is inspired by the methodology described by McLean (2010) where volatility is calculated by orthogonalising returns on the market proxy.

Such a methodology implies that the CAPM is true. The findings lead to a definite area of further research that relates to defining a cleaner proxy for idiosyncratic risk on the JSE by evaluating the various proxies utilized in literature. Unfortunately, this is beyond the scope of this study and therefore, one can conclude that the low volatility premium does not seem to be a significant stylistic factor on the JSE and furthermore, does not drive the cross-sectional variation in share returns. Lastly, currency beta, as defined originally by Barr and Kantor (2005), also achieved mixed results, producing coefficients between -0.16% and 0.24% across the econometric specifications. Within the six regressions that included currency beta as an explanatory variable, only four were statistically significant (at the 10% level) and similarly, only four maintained the correct sign as described by the findings of Page, Britten and Auret (2015).

6.7. CHAPTER SUMMARY

The intention of the chapter was to determine whether momentum is a priced factor on the cross-section of shares listed on the JSE. Alternatively, the key research question is whether momentum, when considered in a multivariate test setting, drive expected (future) share returns on the JSE? The empirical test deviates from conventional asset pricing tests as the limited number of shares and liquidity constraints on then JSE makes multi-portfolio combination sorts virtually impossible and empirically questionable. The methodology applied is a share-by-share aggregated asset pricing test applied to the sample period January 1997 to June 2015 and considers the top 100 most liquid shares based on both market capitalization and value traded on a semi-annual basis. A number of studies encourage a share based approach to determining factors that drive share returns, such as Roll (1977), Lo and Mackinlay (1990) and Shanken and Weinstein (2006), where all castigated the ever popular Fama and Macbeth (1973) two-pass regression methodology.

The nature of the data allowed for the application of econometric models that capture the potential cross-sectional and time period based heterogeneity. Three models were applied in identical fashion and instead of defining the optimal model; the results were analyzed and consolidated in order to determine the consistency of factor significance in explaining the cross-sectional variation in share returns on the JSE. A number of findings are consistent with prior literature, however a number are unique to the South African market and are therefore novel, adding significantly to the current body of literature related to asset pricing and share returns on the JSE.

The size and value phenomenon, credited to Banz (1981) and Basu (1977), have been evaluated on numerous occasions in South African literature. Consistent with the majority of

international and South African literature, both size, proxied by the natural log of market capitalization and value, proxied by the book-to-market ratio are significant determinants of expected average returns on the JSE. The value and size factors consistently maintained the correct sign and where highly significant irrespective of the econometric model applied. Notably, the evidence presented above is inconsistent with the findings of Page, Britten and Auret (2016) as well as the findings presented in Chapter Five of this study. As described above, a potential reason behind the results could be that the results are describing a 'medium size effect' where medium size companies tend to outperform large companies. As noted, the investable universe was limited to the top 100 shares based on size and value traded, implying a universe that does not contain small and micro-capitalization shares. Therefore, the negative relationship found between market capitalization and expected returns may be limited to the large and medium stratum on the JSE.

The regression results present weak evidence of the liquidity premium on the JSE, where liquidity is proxied by the turnover ratio. Amihud and Mendelson (1986) first considered the presence of a liquidity premium in share returns. The liquidity premium dictates an inverse relationship between liquidity and expected return. Unfortunately, this does not consistently manifest across the econometric specifications. The implication is twofold. Firstly, there may not be a significant liquidity premium on the JSE. Secondly, and more plausibly, turnover may be a weak proxy and the universe of shares is limited to a highly liquid subset, possibly limiting the ability to detect a liquidity premium. The result however is highly consistent with Rouwenhorst (1999) who found that the liquidity premium was virtually non-existent in emerging markets.

Unique to South African literature, more recent pricing anomalies are considered as factors and are tested in a multivariate setting. The low beta and low volatility premium as well as currency risk are included as factors within the various regression specifications. The low beta premium seems to be both significant and priced on the cross-section of shares listed on the JSE, with the relationship between (liquidity adjusted) market beta and expected return being consistently negative and statistically significant. The results are therefore consistent with those of van Rensburg and Robertson (2003), Baker, Bradley and Wurgler (2011) and Frazzini and Pedersen (2014) as *ex ante* (pre-ranking) estimated beta maintains an inverse relationship with expected return. The result has significant implications in terms of the plausibility of applying the CAPM specification on the JSE and more importantly, defines a highly credible investment strategy for practitioners.

Unfortunately, the results are less convincing for the low volatility effect as *ex-ante* estimated idiosyncratic risk fails to maintain a constant relationship with expected returns. The result

may be driven by the methodology applied in estimating univariate volatility and is definitely an area of further research. Currency risk or Rand beta fairs relatively well as an explanatory variable, but fails to maintain complete consistency in terms of sign and significance across the econometric specifications. Barr and Kantor (2005) and more recently, Page, Britten and Auret (2015) found that currency risk, proxied by Rand beta, maintains a negative relationship with expected returns in a univariate setting. The regression results indicate that the majority of coefficients conform to the expected relationship and are statistically significant, yet only at the 10% level.

The core findings of the cross-sectional regression analysis relate to that of momentum. The momentum proxy used in the regression analysis is the six minus one-month cumulative return, consistent with international literature in terms of the general momentum proxy. Like the findings of Chapters Three, Four and Five, the momentum coefficients are consistently positive and significant across the various regressions. More importantly, the regression results further prove that momentum is a significant determinant of cross-sectional variation in average share returns, maintaining statistical significance at the 5% and (more regularly at the) 1% level, irrespective of the econometric specification applied. Further, the momentum coefficients are consistently economically larger on average than the other factor coefficients considered, with the majority in excess of 1%. As discussed, the implication entails that a one unit increase in historical momentum measured over the previous six minus one months' entails an approximate increase in future monthly return of 1% on average.

The results of the regressions therefore answer the very specific question posed at the beginning of this chapter (and throughout this study) regarding the incorporation of momentum within a JSE specific asset-pricing model. The consistency of momentum across specifications and within the separate regressions conducted (using each econometric specifications) provides statistically substantiated proof that momentum is a key component of share returns in that it directly influences the dynamics of data generating process that governs share returns on the JSE. The results directly and succinctly dictate that momentum is as important as value or size when defining a pricing model specific to the JSE and is therefore definitively deserving of incorporation. Additionally, the results also indicate that such a model should also include liquidity-adjusted beta, as the low beta phenomenon is as pervasive as size, value and momentum on the JSE.

The key findings of the chapter therefore fit very well with the results presented in Chapter Five of this study. Chapter Five found that none of the non-momentum factors considered across this study (as well as the van Rensburg (2001) APT factors are able to explain the momentum premium estimated via time-series attribution regressions. The results within the

current chapter indicate that momentum is an independent factor that drives the cross-sectional variation in share returns on the JSE. Therefore, it is logical and consistent that non-momentum factors fail to explain the momentum premium as momentum is itself an independent and consistent factor on the JSE and is a significant driver of the cross-sectional variation in share returns on the JSE.

CHAPTER SEVEN: CONCLUSION AND RECOMMENDATIONS

The study of momentum in share prices, more specifically momentum as an investment style, differs from other stylistic passive investment anomalies considered in finance and investment literature. Like other stylistic factor anomalies, momentum is a relative measure that defines the investment quality of shares on a cross-sectional basis using a pre-defined deterministic metric, much like the book-to-market ratio or idiosyncratic risk. The key difference, however, is that the momentum of a share is defined by the historical time-series cumulative performance measured over a recent historical window, referred to as an estimation period throughout this study. The logical simplicity of applying momentum strategies is met with the significant incongruence with the efficient market hypothesis of Fama (1970) as well as the CAPM of Sharpe (1964), Lintner (1965), Mossin (1965) and Black (1972), Fama- French Three factor model per Fama and French (1992) as well as the arbitrage pricing theory model ("APT") of Chen, Roll and Ross (1986).

The premise of weak form EMH dictates that the information contained in historical share prices cannot be exploited to achieve arbitrage profits, leading to the notion of expected return being solely explained by risk. Both the CAPM and APT (and even the Fama-French three factor model) rely on the principle of risk describing the level of expected return. Momentum however, explicitly and solely relies on the informational content in historical share prices. Furthermore, the expected returns attributable to momentum are difficult to reconcile with an *a priori* risk based explanation. The CAPM, APT and even the Fama-French Three factor model all rationalise expected returns to be driven by some form of risk. The CAPM relies on market risk or beta, the APT on underling economic factors while the Fama-French Three factor model augments the CAPM to encompass value and size risk. A key question that remains is what risk drives momentum?

The theoretical impasse caused by momentum has led to the emergence of behavioural finance, where the forces that cause momentum are driven by market psychology and investor irrationality. A number of studies have developed economic models that incorporate investor irrationality that, under simulation analysis, produce the momentum phenomenon, achieving initial profits that eventually reverse. The basis of this study is of an empirical nature and therefore relies on data in order to prove a series of hypotheses that form the overall research question. The study is therefore limited to determining whether, on the cross-section of shares listed on the JSE, momentum is present, independent and significant. The central limitation relates to testing whether other stylistic anomalies (non-parametric) or factor premiums (parametric) explain momentum. Therefore, this study does not attempt to develop any theoretical premise for the cause or existence of momentum on the JSE, but rather attempts

to determine the existence, independence and prominence of momentum in terms of explaining expected returns. The core research question can be summarised to 'Does momentum drive share returns on the JSE?' In order to answer the core research question, a series of sub-hypotheses and empirical tests were formed and conducted. The logical progression that forms the basis of answering the research question posed is best articulated through a three-step process. Firstly, a plethora of literature has found that momentum in share prices over the short to medium term (between three and 12 months) produces significantly positive excess returns that eventually reverse over holding periods in excess of one year. Proving the presence of momentum and eventual reversal, on a univariate basis, proves that momentum applied as an investment style conforms to international and local literature and confirms the **presence of** momentum on the cross-section of shares in question. Further, the eventual reversal in momentum profits provides evidence in favour of behavioural theories of momentum such as under and overreaction as well as self-attribution bias.

Secondly, the question of **independence** is broached by testing momentum in conjunction with other noted investment styles that have been presented in both international and local literature. In this study, both bivariate portfolio sorts and time-series attribution regressions are applied in order to determine whether non-momentum pricing anomalies, applied as both styles and risk factors, explain the momentum premium. 'Explain' implies that the non-momentum anomalies or factor premiums reduce the profitability or risk-adjusted excess returns of momentum portfolios to the point that they are no longer significantly different from zero.

Lastly, if momentum is found to be both present and independent, the final question of whether momentum drives share returns is considered. The final set of tests applied in this study relies on cross-sectional panel data regressions, replacing the conventional Fama and Macbeth (1973) two-pass regression methodology in order to determine the contribution of momentum to the cross-sectional variation in share returns when tested in conjunction with other priced factors. The outcome of the final test is the provision of proof in favour of momentum being **priced** on the cross-section of shares listed on the JSE.

The logical progression and series of empirical tests described above culminate into a progressive organic answer to the core research question posed. If momentum is present, independent and priced, it will form one of the key principal components that explain and describe share returns on the JSE. The result would be far reaching in reference to both\industry and academics alike. The poor performance of the CAPM in explaining the cross-sectional variation in share returns on the JSE is well known by both practitioners and academics, however, the application of advanced/augmented asset pricing models is still not

universally or locally practiced. Academically, the research of share prices and asset pricing would significantly benefit from the outcomes of this study, proving that momentum is a key independent driver of share returns on the JSE and creating further avenues of future research in the field of financial economics, corporate finance and investment. The mere identification of a significant and independent stylistic factor is yet another finding detrimental to the CAPM and the efficient market hypothesis. Simultaneously, proof in favour of a key variable that describes the cross-sectional variation in share returns adds (significantly) to the current body of South African and emerging market financial economics literature.

The benefits to industry and practitioners could be more drastic, as there is a systematic gap between academic output and practical application seen in industry. The majority of practitioners in South Africa still apply the CAPM when conducting valuations, equity research, private equity transactions and fund attribution analysis. The obvious benefit to defining an appropriate, representative and parsimonious asset pricing and attribution model would the determination and establishment of accurate description of the risk/expected return relationship specific to the JSE and South African market. Additionally, the increased market interest in passive investment strategies, moving away from traditional active asset management, makes the outcomes and results of this study highly pertinent to asset managers and investors alike. The benefits of defining the optimal methodological approach when applying momentum strategies, the optimal combination strategy as well as the interaction between momentum and other non-momentum stylistic factor anomalies provides empirically tested tools to industry practitioners and private investors in delivering superior risk-adjusted (and gross) investment performance.

The section that follows describes a summarised synopsis of the results garnered through the study and Section 7.2 follows with the key findings, conclusions and answer to the key research question and objective.

7.1 SUMMARY OF RESULTS

As described above, the purpose of this study is to determine whether momentum is a priced factor on the JSE, thereby questioning whether momentum transcends being a popularised investment style and is found to describe, and therefore contribute, to the cross-sectional variation in share returns. The section that follows provides a synopsis of the tests and findings of this study, describing the significant outcomes required in answering the research question posed.

Chapter Three of this study considered univariate tests of momentum, where, like Jegadeesh and Titman (1993), momentum portfolio simulations were conducted allowing for variations in both portfolio estimation and holding periods. In relation to the research question, the purpose of the univariate tests was to ascertain whether the momentum premium is both present and significant on the JSE. Additionally, a number of methodological augmentations were considered in order to determine the sensitivity of momentum profits to portfolio weighting, short-term reversal, micro-structure effects, transaction costs and liquidity constraints.

The results of the univariate momentum sorts indicated that momentum is highly sensitive to the weighting methodology applied, where equally weighted momentum excess returns superseded their value weighted counterparts. As described in Table 3.4, equivalent equally weighted momentum portfolios produce monthly returns that are 0.38% higher when compared to their value-weighted counterparts. Furthermore, out of the 144 equally weighted portfolio simulations, 110 produced positive excess returns that are significantly different from zero at the 5% level. In comparison, only 25 out of the 144 market capitalization momentum portfolios produced positive excess returns that are significant at the 5% level.

A further finding related to the application of a single month gap between portfolio estimation and holding period. Typically across the South African momentum literature, the majority of studies failed to consider micro-structure effects and the application of allowing for a gap between portfolio estimation and investment. The results presented indicate that momentum profits on the JSE react positively to the allowance of a one month gap, implying that microstructure effects and short-term reversal are present and negatively affect momentum returns. Assuming equal weighting, the application of a single month gap between portfolio estimation and holding periods increased excess momentum returns (across all simulations) from 1.209% to 1.294% per month on average. Moreover, the positive result was largely confined to the extreme holding periods of three and twelve months, equating to an additional 0.156% and 0.196% per month over their ‘no-gap’ counterparts. More interestingly, the effect of allowing a gap between portfolio estimation and holding periods was far more profound on the market capitalization weighted momentum portfolios with the ‘gapped’ value-weighted portfolio returns superseding their non-gapped counterparts by 0.149% per month on average and is significant at the 5% level.

The sensitivity of momentum to the direct (proxied by price) and indirect trading costs (liquidity proxied by a combination of zero daily trades and turnover) associated with the underlying universe of shares is unique to the South African literature. Firstly, the underlying trading costs of constituent shares within portfolio sorts significantly affects momentum profits negatively, consistent with the limits to arbitrage hypothesis of Pontiff (1996). In equally weighted sorts,

79% of the lenient price filter portfolio simulations outperform their most stringent counterparts by 0.143% per month and the difference is significant at the 5% level. The effect is exacerbated when applying value weighting with 88% of the lenient price filter simulations exceeding their stringent portfolio counterparts by 0.108% per month, with the difference being significant at the 5% level.

Univariate momentums sensitivity to liquidity seems confined to holding periods beyond six months, consistent with liquidity maintaining a positive relationship with reversal as per Lee and Swaminathan (2000). Under both weighting methodologies, momentum profits seem to maintain a positive relationship with liquidity between portfolio holding periods of three and six months. The relationship however reverses in portfolio holding periods of nine and twelve months where momentum excess returns tend to display a negative relationship with liquidity. The results are consistent with the findings of Lee and Swaminathan (1990) as more liquid winners and losers tend to reverse at faster rate than their illiquid counterparts. The result therefore indicates that at longer holding periods, lower liquidity momentum excess returns are less sensitive to reversal while the inverse is true for high liquidity winner and loser shares.

Lastly, consistent with Jegadeesh and Titman (1993, 2001), momentum profits on the JSE do eventually reverse, however, the reversal is limited in that loser shares fail to significantly outperform winners over holding periods in excess of a year. Assuming equal weighting, loser shares only outperform winner shares at holding periods in excess of 36 months. At a holding period of 60 months, extreme loser shares outperform their winner counterparts by 0.17% per month, however the differential is not significantly different from zero. The results of the value weighted long-term reversal sorts are highly consistent with those of the equally weighted tests as value weighting exacerbates the reversal of both winner and loser shares. At a portfolio holding period of 60 months, extreme loser shares outperform their extreme winner counterparts by 0.38% per month on average, implying an excess outperformance of 0.2% per month over the equivalent equally weighted reversal portfolios.

A further finding relates to the sensitivity of reversal portfolio returns to price and liquidity effects. In contrast to momentum, reversal portfolios are insensitive to price filters yet highly sensitive to liquidity. Under the assumption of equal weighting, the high liquidity long term reversal excess returns exceed their low liquidity counterparts by 0.3% per month on average and the difference is significant at the 5% level. The effect is more extreme under the assumption of market capitalization weighting, where highly liquid long-term reversal portfolios outperform their less liquid counterparts by 0.18% per month on average and the difference is significant at the 1% level. Notably, even though the results clearly indicate that over long horizons periods in excess of 24 months, extreme loser shares tend to outperform extreme

winners, the excess return of loser over winner shares is not significantly different from zero. As described previously, a potential reason behind the non-significant performance may be due to the buy-and-hold methodology applied, as suggested by Conrad and Kaul (1993), where the authors found that applying a buy-and-hold methodology significantly reduces the 'paper' profits associated with applying long-term reversal strategies. The results of the univariate analysis are unique to the South Africa literature, specifically in terms of the methodological implications of weighting, calculation of portfolio returns, liquidity, trading costs and microstructure effects. Most importantly, the findings indicate unequivocally that momentum is both present and significant on a univariate basis, when applied on the cross-section of shares listed on the JSE over the period January 1992 to June 2015.

Chapter Four considered the interaction between momentum and non-momentum factors on the JSE by applying bivariate dependent and independent sort procedures. The six non-momentum factors applied across the study include size proxied by market capitalization, value proxied by the book-to-market ratio, liquidity proxied by turnover, liquidity adjusted market beta, idiosyncratic risk and currency risk. Notably, the primary purpose of the bivariate tests was to determine both independence and interaction of the non-momentum factors with momentum on the JSE. Secondly, in order to account for the limited size and investable universe of shares listed the JSE, two portfolio sorting methodologies were applied. The first was the conventional independent bivariate sort procedure where shares are sorted independently into one of nine portfolios based on three momentum and the non-momentum factor tercile portfolios using 33rd / 66th percentile breakpoints. The second methodology was dependent in nature in that shares were initially sorted into one of five portfolios based on historical momentum and then assigned initial portfolio weights based on the non-momentum factor applied through the application of a dynamic weighting methodology that mimics the non-momentum factor premium within the momentum quintile portfolios.

The results of the independent and dependent sorts on size and momentum indicated that momentum portrays a marginally negative relationship with size, somewhat consistent with international literature such as Jegadeesh and Titman (1993) and Rouwenhorst (1998). In independent sorts, the highest performing momentum premium was found in the medium size tercile, achieving an excess momentum premium of 0.886% per month, while the smallest size tercile marginally outperformed the biggest size tercile, achieving an excess return of 0.747% against 0.740% per month. The dependent sort results indicated that when applying a dynamic weighting strategy that up weights small market capitalization winners and high market capitalization losers (in the extreme quintile portfolios), the excess momentum premium marginally outperforms the equivalent equal and value weighted momentum premiums by 17

and 15 basis points per month, respectively. The implication of the dependent results is that the effect of mimicking the small size premium through the application of a dynamic weighting methodology results in improved momentum excess returns over the simplistic equal and value based weighting methodologies.

The next non-momentum factor explored was the value premium, accredited to Basu (1977) and popularised by Fama and French (1992, 1993). Asness (1997) considered the relationship between momentum and value and hypothesized that value should maintain a negative relationship with momentum as momentum shares are typically growth shares while loser shares are typically value shares. The results of the independent sorts on momentum and value were highly consistent with those of Asness (1997) and thereby inconsistent with those of Fraser and Page (2000), specifically when focusing on the respective excess return factor premiums. In terms of momentum, the highest momentum premium was achieved in the growth tercile, producing a significant monthly excess return of 1.402%. The momentum premium decreased monotonically when moving from the extreme growth to the extreme value tercile, producing an insignificant excess return of 0.416% per month in the value tercile.

Interestingly, when focusing solely on the long-only portfolios, the results were highly consistent with those of Fraser and Page (2000) as the value-winner portfolio achieved the highest gross-return of 1.478% per month while the growth-winner portfolio achieved the lowest monthly return of 1.284%. The implication of the results is that on an excess return basis, the results are highly consistent with those of Asness (1997), yet the result is largely driven by the short position in the extreme loser portfolio. The dependent sort results confirmed the findings of the independent sorts on value and momentum as the dynamic weighting methodology that mimics the value premium across the momentum quintile portfolios underperformed both the equivalent equal and value weighted momentum quintile excess returns. The value premium weighted momentum premium achieved an average monthly excess return of 1.38%, underperforming both the equal and value weighted momentum premiums by 0.153% and 0.155% per month on average respectively. The results therefore indicate that momentum and value on the JSE display a negative interaction, so much so that in bivariate independent sorts, the effect negates the respective counterpart premium to the point of non-significance.

The next set of bivariate sorts considered the interaction between momentum and liquidity, proxied by turnover. A number of studies had considered the interaction between momentum and liquidity, specifically Lee and Swaminathan (2000) who found that the momentum premium was positively related to liquidity, implying non-consistency with the typical notion of a liquidity premium. Page, Britten and Auret (2013) found that momentum on the JSE

maintained a positive relationship with liquidity (proxied by volume) and hypothesised that the relationship was consistent with the behavioural concept of 'herding' where liquidity and momentum reinforced each other, thereby resulting in a feedback loop where momentum increases liquidity and liquidity increases momentum over horizons of between three and twelve months.

The results of the independent sorts on momentum and liquidity (proxied by turnover) indicated that momentum is independent of liquidity on the JSE as irrespective of the liquidity tercile, the momentum premium was both positive and significant. Considering interaction, the results of the independent bivariate sorts indicated that the momentum premium on the JSE displays a negative relationship with liquidity, with the low liquidity momentum premium outperforming both its medium and high liquidity tercile counterparts, achieving a monthly excess return of 1.235% compared 0.788% and 0.768% respectively. Importantly, when decomposing the source of the interaction, the majority of the outperformance of the low liquidity momentum premium was driven by the short position in the low turnover loser portfolio where the latter produced the lowest monthly return across all of the portfolios of 0.116% per month.

The nature of the liquidity premium and its inconsistency with momentum was taken into account when conducting dependent sorts. Typically, the liquidity premium dictates that low liquidity shares are expected to outperform their high liquidity counterparts, thereby compensating investors for bearing liquidity risk (see Amihud and Mendelson (1986) and Ibbotson *et al.* (2013)). However, a number of studies have noted that momentum maintains an inverse relationship with the typical liquidity premium. Therefore, in order to account for the empirical idiosyncrasy, two dependent sorts were conducted where the first considered the typical liquidity premium where the dynamic weighting strategy up weighted low (high) liquidity winners (losers) while the second applied the inverse liquidity premium by up weighting high (low) liquidity winner (loser) shares.

The results of the dependent sorts were highly consistent with those of the independent sorts, as the typical liquidity premium weighted momentum premium produced an average monthly return of 1.78%, outperforming both the equal and value weighted momentum premiums by 2.93% and 2.92% per annum respectively. Conversely, the inverse liquidity premium produced a monthly average return of 1.45%, underperforming the equal and value weighted momentum premiums by 0.95% and 0.96% per annum respectively. The implication of the results therefore imply that momentum on the JSE maintains a positive relationship with liquidity on a long-only basis, yet when applying a zero-cost momentum strategy, the relationship inverts and displays a positive relationship with the typical liquidity premium.

Chapter Four specifically differentiated between the non-momentum factor proxies determined via regression analysis, specifically market beta, idiosyncratic risk estimated via orthogonalization on the market proxy (J203 ALSI) and currency risk proxied by exchange rate beta. The reason for differentiation related to the estimation procedure as well as the sample period being narrowed in order to allow for an historical regression window of between 36 and 60 months. The first regressed factor considered was idiosyncratic risk where a number of studies have found that momentum is independent of the low volatility premium and is expected to maintain and negative interaction with volatility. McLean (2010) found that momentum could not be explained by idiosyncratic risk indicating that the 'limits to arbitrage' hypothesis failed to explain the momentum premium. The results of the independent sorts on momentum and idiosyncratic risk indicated that momentum and idiosyncratic risk seemed to maintain a significantly positive relationship, with the momentum premium being highest in the highest volatility tercile, achieving an average return of 1.749% per month. Conversely, the momentum premium in the lowest volatility tercile achieved an excess return of just 0.112% and lacked statistical significance.

The implication of the results is contrary to the findings of the McLean (2010) and more recently, Page, Britten and Auret (2016) as the positive relationship between momentum and idiosyncratic risk implies that momentum is not independent of underlying volatility and therefore potentially explained by the limits to arbitrage hypothesis. The limits to arbitrage hypothesis implies that arbitrageurs or 'smart money' are prevented from arbitraging away mispricing as the underlying factor strategy involves unmanageable levels of volatility that reduce the marginal benefit of engaging in the said strategy. Since arbitrageurs are prevented from benefiting from the mispricing, the mispricing persists and continues to produce significant paper profits. Additionally, the results of the independent sorts can also be linked to the findings of Conrad and Kaul (1998) where the authors found that momentum requires cross-sectional dispersion in means returns as momentum strategies are merely a manifestation of investing in high mean return shares and shorting low mean return shares. The results are therefore consistent with this assertion as the momentum premium is highest in the tercile that displays the highest levels of cross-sectional (and time-series) dispersion, therefore consistent with a risk-based explanation of the momentum premium on the JSE.

The benefit of the dependent sort procedure applied in the study was emphasized when considering the regressed factors. A simple analysis of the extreme portfolios share constituent numbers throughout the independent sort procedure indicated that both the high and low volatility portfolios were prone to low numbers of constituent shares which could result in significant firm-specific bias, noisy returns and deeper impact of outliers. The results of the

dependent sorts were far more consistent with international and local literature as the low volatility premium weighted momentum premium achieved an excess average monthly return of 1.69% per month over the sample period, equating to an additional return of 2.31% and 1.76% per annum over the equal and value weighted premiums respectively. The bivariate dependent dynamic sorts therefore indicated that momentum tends to display a significantly negative relationship with idiosyncratic risk, implying that the limits to arbitrage hypothesis fails to explain the momentum strategy on the JSE and is therefore consistent with the findings of McLean (2010) and more recently, Page, Britten and Auret (2016).

The second regressed non-momentum factor considered was the liquidity adjusted CAPM beta per McClelland *et al.* (2014), with specific emphasis leaning towards the interaction between momentum and the recently popularised low beta phenomenon as described by Frazzini and Pedersen (2013). Van Rensburg and Robertson (2003) alluded to the low beta anomaly as they found that portfolio returns on the JSE display an inverse relationship with *ex ante* estimated betas. There is limited literature on the interaction between momentum and the low beta anomaly, however most, if not all, momentum studies find that both the extreme winner and loser portfolios produced significantly positive market betas, implying an expected inverse relationship between momentum and the low beta phenomenon. The results of the dependent sorts indicated that momentum maintained a positive relationship with market beta (and a negative relationship with the low beta premium) as momentum excess returns decreased monotonically when moving from the high to low beta quintiles. The highest beta quintile produced a momentum excess return of 1.788% per month while the low beta quintile produced the lowest momentum premium of 0.698% per month.

Importantly, momentum was found to be independent of the low beta phenomenon as irrespective of the beta tercile, the momentum premium was both positive and significant. Furthermore, the main source of variation in the momentum premiums seemed to be driven by the short position in the loser portfolio. On a long-only basis, the highest winner return was generated by the low beta winner portfolio, achieving a monthly average return of 1.414%. However, the low beta loser portfolio produced the highest return of 0.716% per month across the beta terciles, compared to -0.409% per month achieved by the high beta loser portfolio. The implication of the findings was therefore that the negative interaction between momentum and the low beta phenomenon was driven by the low beta phenomenon being specifically robust in the loser tercile.

Dependent sorts were then conducted applying the dynamic factor weighting methodology where low (high) beta winner (loser) shares were assigned the highest in-portfolio weightings in order to mimic the low beta effect in quintile momentum portfolio sorts. The results of the

bivariate sorts were largely consistent with long-only performance of the independent sorts as the low beta weighted momentum premium produced an average monthly return of 1.71% and was significant at the 1% level. The low beta weighted momentum premium was then compared to the equivalent equal and value weighted momentum premiums in order to determine the interaction between the factors. The results of the comparison were inconsistent with those presented in the independent sorts as the low beta weighted momentum premium produced returns that were 2.52% and 1.97% per annum greater than the equivalent equal and value weighted momentum premiums, implying a significantly positive interaction between momentum and the low beta premium.

The final non-momentum regressed factor considered was currency risk attributable to Barr and Kantor (2005) and more recently Page, Britten and Auret (2015). Page, Britten and Auret (2015) found that share returns maintained a positive relationship with currency risk and therefore an inverse relationship with currency beta (a positive currency beta implied an inverse relationship with the USD/ZAR exchange rate and was dubbed a Rand Hedge share while the inverse was labelled a Rand Tracker share). The results of the dual independent sorts on momentum and currency risk indicated that momentum on the JSE is independent of currency risk as irrespective of the currency risk tercile, the momentum premium was positive and significant. Interestingly, when considering the interaction between the two factors, momentum seemed to display a negative relationship with currency risk as the highest momentum premium was found in the Rand Hedge tercile, producing a monthly return of 1.676%. Additionally, the source of the positive performance seemed to emanate from both the long and short positions in the rand hedge winner and loser portfolios. The rand hedge winner portfolio produced the highest return of 1.547% per month while the rand hedge loser portfolio produced the lowest monthly return of -0.129%.

The inconsistency of the results of independent sorts with the findings presented by Page, Britten and Auret (2015) necessitated the two sets of dynamic sorts being conducted where the first applied a dynamic weighting strategy that up weighted Rand Hedge winner shares and Rand Tracker losers while the second up weighted Rand Tracker winner shares and Rand Hedge losers. The latter weighting methodology was in effect the application of the Rand Tracker premium as described by Page, Britten and Auret (2015). The result of the Rand Hedge weighted momentum premium was an average monthly momentum premium of 1.05% and was significant at the 5% premium. Contrariwise, the Rand Tracker weighted momentum premium achieved a monthly return of 1.6%. When comparing the Rand Tracker and Rand Hedge weighted momentum premiums to the equivalent equal and value weighted estimations, the former outperformed the simplistic weighting strategies by 1.17% and 0.62%

per annum while the latter underperformed by 5.46% and 6.00% per annum. The results of the dependent sorts were therefore highly consistent with the findings of Page, Britten and Auret (2015) and inconsistent with the results of the independent sorts that applied currency risk as a non-momentum factor.

The results of Chapter Four indicated that the momentum premium is largely independent of non-momentum factors on the JSE and indirectly emphasized the requirement of methodological variations necessary in determining both independence and interaction between factor pricing strategies. Barring the evidence related to momentum and value, none of the sorts presented in Chapter Four conclusively proved (where conclusive implies consistent results between both the independent and dependent sorting methodologies applied) that momentum is driven by other pricing anomalies on the JSE.

A distinct benefit of the bivariate sorting methodology applied is that the tests are innately non-parametric and unconditional. The obvious limitation of the bivariate sorts is that tests are limited to singular co-factor analyses and the addition of further factors in multivariate sorting tests is implausible given the liquidity and size of the JSE. Therefore, a natural extension of the test was the transition from non-linear unconditional bivariate tests to a multivariate linear (conditional) setting that allows for the simultaneous evaluation of non-momentum factors within a single testal framework. Chapter Five considered the momentum premium and quintile portfolios as dependent variables and utilised time-series attribution regressions in order to determine whether the non-momentum factors (independent variables) considered in Chapter Four simultaneously explain the momentum premium on the JSE.

Chapter Five considered four attribution models that included the pure market model, the Fama-French Three Factor model, a attribution model that considered the low-beta, low volatility, liquidity and currency risk factors and lastly, the van Rensburg (2002) APT factor model. For each of the regressions run, three sets of regressions were conducted where momentum portfolios returns were calculated assuming equal, market capitalization and momentum (relative strength) weightings. Lastly, for each of the regression models applied, GRS statistics per Gibbons, Ross and Shanken (1989) were calculated in order to determine whether the applied factor premiums successfully explained the cross-sectional variation in time-series alphas of the underlying momentum portfolios. The total number of time-series regressions run amounted to 60; considering five momentum portfolios, three weighting methodologies and four attribution models.

The results of the market model (CAPM) time-series regressions clearly indicated that the market risk premium on the JSE fails to explain the momentum premium. The equally weighted

winner portfolio produced a significant time-series alpha of 0.53% per month while the loser portfolio achieved a significant -0.95% per month. The fictional, zero cost excess momentum premium was 1.48% per month, implying an annual risk-adjusted excess return of 17.7% that is significantly different from zero at the 1% level. Furthermore, the GRS statistic rejected the null hypothesis at the 1% level, implying that the market model fails to jointly explain the variation in equally weighted momentum alphas. The results of the value weighted momentum portfolios regression indicated that the extreme winner portfolio produces a significant monthly return of 0.61% per month while the extreme loser portfolio produced a significant monthly return of -0.94% resulting in a significant excess momentum premium of 1.55% per month. Similarly, the GRS statistic indicated that the variation in market capitalization weighted momentum portfolios could not be explained by the market risk premium on the JSE.

The results of the weighted relative strength momentum portfolio market model attribution regressions were highly consistent with those of the equal and value weighted momentum portfolios. The extreme winner portfolio achieved a risk-adjusted return of 0.63% per month while the extreme loser portfolio achieved a significantly negative risk-adjusted return of -0.99% per month, resulting in a significant risk-adjusted excess return of 1.62% per month on average. The results of the market model regression clearly indicated that, unlike the results described in Chapter Three, on a risk-adjusted basis, value weighted momentum returns outperformed equal weighted returns, while the best momentum premium was produced by the relative strength momentum weighted momentum portfolios. A further test was conducted to determine the relative contribution of the long and short positions in the extreme winner and loser portfolios to the achieved zero cost portfolio alpha. The results were highly consistent with Lesmond *et al.* (2004) as approximately 62% of the total momentum premium was attributable to the short position in the extreme loser portfolios across the three weighting schematics applied.

The results of the Fama-French Three Factor attribution regressions were largely consistent with international literature. The equally weighted momentum portfolios produced time-series alphas that decreased monotonically when moving from the extreme winner to the extreme loser portfolio, resulting in a significant excess risk-adjusted momentum premium of 1.54% per month. Interestingly, all of the momentum portfolios seemed to load positively on the size factor. Conversely, all of the equally weighted momentum portfolios (barring portfolio three) loaded negatively on the value premium. The GRS statistic rejected the null of time-series alphas being jointly equal to zero implying that the Fama-French Three factor model failed to explain the equally weighted momentum premium on the JSE.

The results of the attribution regressions conducted on the value-weighted momentum portfolios were highly consistent with those of equally weighted. Time-series alphas decreased monotonically when moving from the extreme winner to extreme loser portfolios, culminating in an excess risk-adjusted value weighted momentum premium of 1.6% per month. Once again, all of the momentum portfolios seemed to load positively on the small size premium while portfolios one and two achieved economically lower value factor loadings than portfolios three to five, consistent with the assertions of Asness (1997) who found that extreme winner shares were generally growth shares while extreme loser shares were generally value shares. Lastly, the GRS statistic confirmed that the Fama-French factors fail to explain the market capitalization weighted momentum premium on the JSE by rejecting the null at the 1% level.

The results of the final set of Fama-French Three factor attribution regressions were run on the weighted relative strength momentum portfolios. The extreme winner momentum portfolio produced a risk-adjusted return of 0.86% per month while the extreme loser portfolio produced a significantly negative portfolio alpha of -0.91% per month, resulting in a risk-adjusted weighted relative strength momentum premium of 1.77% per month. Consistent with the results of the market model time-series regressions, the weighted relative strength momentum premium superseded the value weighted momentum premium, while the value weighted superseded the equal weighted momentum premium.

The GRS statistic rejected the null of portfolio alphas being jointly equal to zero at the 1% level significance, implying that the Fama-French factors fail to explain the variation in relative strength weighted momentum portfolio alphas. In fact, a further finding that is highly consistent with international literature is the effect of applying the Fama-French three factor model in describing momentum returns. Across each of the weighting methodologies applied, the Fama-French Three Factor portfolio alphas were consistently higher than those estimated via the market model, implying that the Fama-French factors tend to artificially augment the momentum premium, pointing to model misspecification. Lastly, the decomposition of the momentum premium (when applying the Fama-French Three factor model) indicated that approximately only 55% of the momentum premium is attributable to the short position in the extreme loser portfolio, implying a reduction in the contribution of the short position in the extreme loser portfolio when compared to the pure market model attribution regressions.

The next set of attribution regressions applied the remaining non-momentum factors used in Chapter Four of the study, namely the low beta, low volatility, liquidity and currency risk premiums. The regression results on the equally weighted momentum portfolios indicated that the extreme winner portfolio achieved a risk-adjusted alpha of 0.83% month while the extreme loser portfolio -0.79%, resulting in a risk-adjusted equally weighted momentum return premium

of 1.62% per month that is significant at the 1% level. Furthermore, the GRS test statistic indicated that the factor premiums applied failed to explain the equally weighted momentum premium on the JSE. The results were virtually identical when utilising market capitalization weighted momentum returns as portfolio alphas decreased monotonically when moving from the extreme winner to extreme loser portfolios, resulting in a risk-adjusted zero cost momentum premium of 1.69% per month and was significant at the 1% level. Similarly, in the weighted relative strength momentum regressions, the excess return premium achieved amounted to 2.04% per month while the GRS statistic strongly rejected (at the 1% level) the null of the factor premiums applied describing the cross-sectional variation in momentum portfolio alphas.

Interestingly, the only significant factor seemed to be the low volatility premium, where across the weighting strategies, extreme winners produced economically smaller factor loadings than extreme losers, implying that winner shares tend to be relatively higher volatility shares than their loser counterparts yet, idiosyncratic risk fails to explain the momentum premium. The result is therefore highly consistent with those of McLean (2010) and Page, Britten and Auret (2016) who both found that idiosyncratic risk and the Limits to Arbitrage hypothesis fails to explain the momentum premium. An additional interesting finding was that the time-series alphas produced via the five factor model were economically higher than both the market and Fama-French Three factor models applied, while a further shift was found in the relative contribution of the long and short positions in the extreme winner and loser portfolios. The results of the relative contribution analysis indicated that the long-position in extreme winner shares provided 60.89% of the total momentum premium while only 45.10% is garnered by the short position on average, indicating that the hypothesis of Lesmond *et al.* (2004) seems highly sensitive to the underlying attribution model applied.

The final set of attribution regressions were conducted applying the suggested APT factors of van Rensburg (2002), namely the excess returns on the FINDI and RESI. The attribution regressions conducted on the equally weighted momentum portfolios indicated that portfolio alphas decreased monotonically when moving from the extreme winner to extreme loser portfolios, resulting in a risk-adjusted excess return of 1.36% per month that was significant at the 1% level. The results indicated that there was little variation in FINDI factor loadings across the momentum portfolios, yet the FINDI factor loadings were economically larger than those of the RESI. The GRS test statistic rejected the null hypothesis of the FINDI and RESI premiums explaining the equally weighted momentum premium on the cross-section of shares listed on the JSE.

The results of the value-weighted attribution regressions applying the van Rensburg APT factors were effectively identical to those of the equal weighted, with portfolio alphas decreasing monotonically when moving from the extreme winner to the extreme loser portfolios. The zero cost value weighted (risk-adjusted) excess momentum premium amounted to 1.43% per month and was significant at the 1% level. Once again, the GRS statistic strongly rejected the null of the FINDI and RESI premiums explaining the value-weighted momentum premium on the JSE. Lastly, the results of the weighted relative strength momentum attribution regressions indicated that both the RESI and FINDI fail to explain the momentum weighted momentum premium on the JSE. The excess risk-adjusted momentum premium achieved was 1.49% per month and significant at the 5% level while the GRS test statistic rejected the null of portfolio alphas being jointly equal to zero at the 5% level of significance.

Consistent with the prior models applied, once again the highest momentum premium was found when applying the weighted relative strength weighting, then market capitalization and lastly equally weighted portfolio weighting mechanisms. The results further indicated that the van Rensburg (2002) APT factors failed to explain the momentum premium on the JSE. Analysis of the relative contribution of the long and short position were also inconsistent with the findings of Lesmond *et al.* (2004) as the results indicated that 53.29% of the momentum premium emanated from the long position in the extreme winner portfolio and only 46.71% from the extreme loser portfolio.

A final set of regressions were run in order to determine whether any combination of the factor premiums considered was able to explain the momentum premium on the JSE. The methodology applied was a backward elimination step-wise regression. The effect of applying all the factors within a single regression resulted in a contrary result to that which would be expected in that market capitalization weighted momentum risk-adjusted profits increased to the highest levels seen across the attribution tests. The extreme winner portfolio achieved a time-series alpha of 1.54% per month and was highly significant at the 1% loading significantly on the JSE, FINDI, RESI, low volatility and size. The extreme loser portfolio achieved a time-series alpha of -1.7% per month, was highly significant at the 1% level and loaded significantly on the FINDI, RESI and size premiums. The zero cost momentum premium was 3.04% per month, equating to an annual return of 36.45%. The implication of the results were therefore that even when foregoing parsimony, the application of multiple non-momentum factors tends to result in the exacerbating the momentum premium to levels in excess of their non-risk adjusted gross returns.

In summary, the results of Chapter Five significantly contribute to the current body of knowledge as they clearly indicate that under the assumption of a linear, conditional framework, none of the non-momentum factor premiums applied in the study are adequately able to explain the cross-sectional variation in momentum portfolios and therefore the momentum premium on the JSE. Moreover, the results clearly indicate that the optimal weighting mechanism in terms of achieving risk-adjusted excess returns is the weighted relative strength ranking mechanism, which consistently dominated both the value and equally weighted momentum premiums.

A further important result relates to the assertions of Lesmond *et al.* (2004) and to some extent Fama and French (1996). Firstly, the results undoubtedly indicate that any attempt to augment attribution models with additional factors produces converse results as the momentum premium increases. Similarly, the effect is also seen in the relative contribution of the long and short positions to the momentum premium, where the inclusion of additional non-momentum factors results in the shift from the short position to the long position being the main contributor to the achieved momentum premium. The results therefore portray a clear finding in terms of the momentum premium on the JSE where the effect of additional non-momentum factors simply increases the model misspecification and artificially increases the risk-adjusted momentum premium beyond its nominal, gross, non-risk adjusted profits.

The implication of the results therefore directly indicate that the momentum premium on the JSE cannot be explained by non-momentum factor premiums. The logical progression of the test was therefore extended to the final set of tests which intended to determine whether momentum itself is a priced factor on the JSE. A key difference in the approach applied between Chapters Five and Six is that momentum was first considered the dependent variable in time-series attribution regressions, yet in Chapter Six, share price momentum is considered with the other non-momentum factors as independent explanatory variable.

To reiterate, the results of Chapters Three to Five definitively prove that momentum on the cross-section of shares listed on the JSE is both present, significantly positive and unequivocally independent on both a parametric (conditional and risk-adjusted) and non-parametric (unconditional and gross) level. The culmination of results imply that momentum seems to meet all the criteria necessary for inclusion within an asset pricing specification applicable to the cross-section of shares listed on the JSE. The pen-ultimate test therefore requires effectively testing whether momentum is indeed priced, by ascertaining whether momentum explains, contributes and maintains a causal relationship with expected returns on the cross-section of shares listed on the JSE. The generally accepted international methodology applied in testing (in a multivariate setting) whether a stylistic factor is ‘priced’ is

the Fama and Macbeth (1973) two-pass regression. This study applies a share-by-share cross-sectional analysis and considers a number of econometric models in order to mitigate the potential biases that arise from conducting simultaneous sorts on stylistic factors when using a highly constrained, illiquid small universe of shares as is the case with the JSE relative to international and developed equity markets.

By international standards, the JSE is both small and illiquid, thereby limiting the plausibility of conducting simultaneous sorts on various styles which is a pre-requisite of Fama-Macbeth regressions. In order to maintain the parametric linear nature and efficiency of the test as well as the essence of the research question, an alternate methodology is applied where panel data based econometric models that adjust for heterogeneity, serial correlation and multicollinearity in priced factors are applied. A corollary to the central research question is that the results of Chapter Six provide significant insight into the stylistic factors that drive share returns on the JSE. Indeed, momentum is the central style in question, however, the findings are far reaching in that they also describe which of the non-momentum factors considered truly explain and drive expected share returns on the JSE.

Chapter Six, which is the definitive chapter of the study, presented the results of the panel regressions, applying three panel data econometric specifications, specifically the pooled least squares, fixed effects and random effects models. The dependent variable applied in the cross-sectional regression analysis is the share specific average monthly return measured over the previous six months while the independent variables applied were the lagged values of size proxied by market capitalization, value proxied by the median book-to-market ratio, liquidity proxied by turnover, momentum proxied by the historical cumulative six minus one month return, idiosyncratic risk, market beta and currency beta. For each of the econometric models applied, five regressions were run where the first specification considered size and value (Fama and French (1992) factors), the second; size, value and momentum (Carhart Model (1997)), the third; size, value, momentum and liquidity, the fourth market beta, idiosyncratic risk and currency risk and lastly, the fifth regression that considers all of factors described in regressions one to four.

Focusing on regression five, the results of the pooled OLS specification indicated that value, size, momentum, liquidity, market beta and currency beta explain share returns on the JSE. Both the size and value coefficients were significant and the correct sign, implying that a single unit increase in the median book-to-market ratio is expected to result in an increase in expected average monthly return of 0.28% while a unit decrease in market capitalization results in an increase in average monthly return of 0.29% and therefore consistent with the findings of Basiewicz and Auret (2009), Gilbert *et al.* (2011) and more recently Page and Auret

(2013). The sign of the liquidity premium was positive, implying an inverse liquidity premium on the JSE and that a one unit increase in turnover is expected to be met with an increase in monthly average return of 0.14%. The liquidity coefficient is highly consistent with the findings of Rouwenhorst (1999) as the author found an inverse liquidity premium in emerging markets.

The market beta coefficient was significantly negative, providing evidence of the low beta premium on the JSE, consistent with the findings of Frazzini and Pedersen (2013) while the currency beta coefficient was positive and significant at the 10% level, yet inconsistent with the findings with Page, Britten and Auret (2015) as the result indicated that a one unit increase in currency beta is expected to manifest in an increase in average monthly return of 0.24%. Most importantly, the momentum coefficient was positive and maintained significance across the various regressions, indicating that at minimum, a one unit increase in cumulative return over the previous six (minus one) months results in an increased average monthly return of 0.91%. The results are therefore highly consistent with the findings of van Rensburg (2001), Muller and Ward (2013) and more recently Page, Britten and Auret (2016) as all found a significant and positive momentum premium on the cross-section of shares listed on the JSE.

Due to the panel nature of the data, the possibility of heterogeneity being present across both individual shares and time was considered and mitigated via the application of the fixed effects model. The fixed effects model corrects for potential heterogeneity across individual shares as the model assumes that heterogeneous differences are captured in the intercept term. Importantly, when testing for the presence of fixed effects, the likelihood ratio test indicated that the data presented both time-series and cross-sectional fixed effects and therefore both types of fixed effects were accounted for in the regression analysis. Focusing on regression fives results, both the size and value coefficients were significantly positive and negative, indicating that a one unit increase in the median book-to-market ratio is expected to result in an increased average monthly return of 0.3% while a one unit decrease in the natural log of market capitalization is expected to result in a 1.63% increase in monthly average return (effectively indicated a size premium that is quadruple the size of the POLS coefficient). The liquidity coefficient was again significant at the 10% level and portrayed the correct sign, indicating that a one unit increase in turnover is expected to be met with a -0.2% decrease in average monthly return. The result was therefore consistent with those of Amihud and Mendelson (1986) and Ibbotson *et al.* (2013).

Once again, the market beta coefficient was significantly negative, indicating that a one unit increase in market beta is expected to generate a 0.75% decrease in average monthly return. Both the volatility and currency risk coefficients were not significantly different from zero, however the currency coefficient was consistent with the findings of Page, Britten and Auret

(2015) as the coefficient indicated that a one unit increase in currency beta is expected to reduce expected monthly average returns by -0.16% on average. Lastly, and most importantly, the momentum coefficient was significantly positive and marginally higher than the POLS results, where a single unit increase in historical momentum is expected to result in a 1.02% increase in monthly average return. Furthermore, irrespective of the variables included within the regression specification, the momentum coefficient did not drop below 1%, and therefore is highly consistent with the unconditional results presented in Chapter Three.

The final set of regressions applied the random effects model that corrects for heterogeneity across individual shares and time by incorporating a random component in the error term as opposed to the intercept. The benefits of the random effects specification are that the model assumes that heterogeneous effects are indeed 'random' across individuals and time, therefore highly consistent with the random nature of cross-sectional and time-series financial data. Furthermore, the model is estimated using generalised least squares ('GLS') which is found to be more consistent in large samples. The results of regression five are considered where once again, both the value and size coefficients were significant and maintain the correct sign, where a one unit increase in the book-to-market ratio is expected to result in an increase in expected monthly return of 0.26% while a one unit decrease in market capitalization is met with an increase in expected monthly return of 0.16%.

Consistent with both the pooled OLS and fixed effects regression results, the market beta coefficient is negative and significant, indicating that a one unit decrease in market beta is expected to produce a 0.64% increase in monthly expected return. For the first time, the idiosyncratic risk coefficient was both significant and negative, indicating that a one unit increase in idiosyncratic risk is met with a decrease in expected monthly returns of 3.98%. Like the results of the fixed effects model, the currency risk coefficient was significantly negative (at the 10% level) and therefore consistent with the findings of Page, Britten and Auret (2015). The random effects model produced the highest momentum premium of the econometric models, where the momentum coefficient indicated that a single unit increase in the six minus one month momentum results in an expected increase of average monthly return equal to 2.18%.

The results of the panel data cross-sectional regressions were summarised in Table 6.6 where the table describes the factor premium coefficients across the various econometric specifications, the percentage of times the said factor was significant as well as the consistency of the coefficient estimates with both local and international literature. The table clearly indicates that both size and value, proxied by market capitalization and the book-to-market ratio, are significant determinants of the cross-sectional variation in share returns listed

on the JSE, thereby confirming the findings of Basiewicz and Auret (2009, 2010), Gilbert *et al.* (2011) and Page and Auret (2013). Novel results are presented in terms of the low beta anomaly as liquidity adjusted market beta produced a significantly negative coefficient across the regression specifications, presenting clear evidence in favour of the low beta premium on the JSE.

Unfortunately the regression results related to liquidity, idiosyncratic risk and currency risk were less promising. The conventional liquidity premium only manifested in 33% of the regressions, providing evidence consistent with the findings of Rouwenhorst (1999) who found that the liquidity premium is virtually non-existent across emerging markets. Currency risk faired marginally better as it achieved statistical significance in 67% of the regressions in which it featured and was consistent with the findings of Page, Britten and Auret (2015). The results are therefore highly consistent with those expressed in Chapter Five of this study, where it was clearly shown that Rand Tracker shares only marginally outperform their Rand Hedge counterparts. The most disappointing result relates to the low volatility premium. Unfortunately, the low volatility premium only presented itself under the random effects specification and was only significant in regression five (and only at the 5% level).

The key result and a major portion of the answer to the research question posed in this study is noted in the summary results presented in Table 6.6. Analysis of the factor coefficients indicate that the momentum premium is between 1.08% and 2.23% per month on average and is therefore highly consistent with international and local literature. Importantly, of the nine times that momentum featured in the regression analysis, it was statistically significant 100% of the time, eight of which were at the 1% level. Furthermore, the sign of the momentum coefficient was always positive implying that the results are once again highly consistent with international and local literature. The regression analysis therefore clearly indicates that momentum is certainly a priced factor on the cross-section of shares listed on the JSE and provides significant explanatory power in describing share returns even when combined with other pricing anomalies/risk factors.

The results of Chapter Six are therefore highly consistent with those presented in Chapters Three to Five. Irrespective of the econometric specification or the other stylistic factors considered as independent variables within the regression specification, the historical six minus one month cumulative return, i.e. momentum, was a significantly positive determinant of expected share returns on the JSE. Additionally, the momentum premium was found to be the economically highest (on average) among all of the styles considered, producing coefficients in excess of 1%, consistent with the findings seen in the previous chapters. The results of the cross-sectional regressions further depict a JSE specific pricing model that

effectively takes the form of a Carhart (1997) model that is augmented by the “BAB” factor of Frazzini and Pedersen (2014). An obvious line of future research would be testing this pricing model on the cross-section of shares listed on the JSE, either on fictitious or traded portfolios, in order to determine its ability in describing excess returns. Importantly, the key finding is that the cross-sectional regression results clearly indicate that irrespective of the underlying drivers of momentum on the JSE, momentum itself is a priced factor that deserves inclusion within a factor pricing framework and exclusion thereof would amount to clear model misspecification. The section that follows provides the conclusion of the study by articulating clear and concise answers to the key research questions and sub hypotheses articulated in the introductory chapters.

7.2 CONCLUSION

The purpose and aim of this study was described in Chapter One and rearticulated on numerous occasions throughout. Momentum can be considered a ‘unique’ stylistic factor anomaly as it relies solely on a shares trajectory over short holding periods. It differs significantly from other factor anomalies as it is almost impossible to articulate that momentum is driven by risk, hence leading to a new realm of finance that relaxes the tenet of investor rationality. This study applied an approach similar to the likes of Chen, Roll and Ross (1986), Fama and French (1992) and Carhart (1997) where ‘empirical testing and identification’ supersedes the requirement of an *a priori* theoretical explanation. In truth, this study applies a number of non-parametric and parametric ‘risk’ based tests to explain momentum. Importantly, there are two possible conclusions. Theoretically, the first would be that momentum is not driven by risk, and therefore through a process of logical elimination, is deemed to be driven by behavioural biases and market irrationality. The second is that non-momentum stylistic factors or risk premiums fail to explain momentum, therefore momentum itself is an independent style that governs share returns and is possibly driven by an unspecified unknown risk. The benefit of applying the latter does not preclude a risk or behavioural based explanation. In fact, it is even possible that a combination of both theories may explain why momentum exists.

The basic theoretical tenet applied in developing the research question at the core of this study is that a factor can still be considered a factor, even without an *a priori* theory explaining its existence. Phrased differently, a style is a factor if it meets three pre-specified criteria, namely that the said factor produces significant profits on both a long-only and zero cost basis, is not explained or reduced by other known factor anomalies and is priced i.e. contributes to the cross-sectional variation in share returns. The question of whether momentum is

compensation for some form of risk is almost immaterial, as the compensatory component of the argument is not in question as proved through a number of empirical tests that momentum provides additional return and risk-adjusted profit. The results of this study indicate that momentum, beyond any reasonable doubt, is highly profitable as a style, is independent of other noted styles and contributes significantly to the cross-sectional variation in expected share returns on the JSE.

Moreover, the results of this study indicate that, since momentum is priced, it deserves inclusion within a factor model that describes share returns on the JSE and that the exclusion of momentum from a pricing model amounts to 'misspecification'. The results presented in this study are not exclusive to the existence of momentum. Firstly, significant findings were made related to the methodological application of momentum strategies pertaining to weighting, liquidity, transaction costs as well as combination strategies. Furthermore, a number of findings relate to the non-momentum styles considered. Firstly, the value premium seems to be significant and present on the cross-section of JSE listed shares, where results were confirmed in both bivariate and cross-sectional tests. The results pertaining to the size effect were mixed. The small size effect on the JSE seems to have been replaced by the 'medium' size effect, where medium size shares in both bivariate and cross-sectional tests seem to provide the highest level of returns. Although this finding is not explored at length in this study, it certainly provides avenues of future research related to the size effect on the JSE.

Consistent with the findings of Rouwenhorst (1999), the liquidity premium on the JSE seems to be non-existent, specifically when liquidity is proxied by turnover. To the best of the authors' knowledge, this study is the first to consider both the low volatility and low beta premium on the JSE. In bivariate tests, both the low volatility premium and low beta effect were significantly positive, producing results consistent with Baker, Bradley and Wurgler (2011) and Frazinni and Pedersen (2014). However, when applying both styles as factors within the cross-sectional pricing regression analysis, the low volatility premium was highly inconsistent and largely superseded by the low beta anomaly. Lastly, the results of currency risk were largely unconvincing when coupled with the other considered styles.

Relating the conclusion to the core research question posed, the series of empirical tests provide evidence in favour of momentum being a priced factor that explains a significant portion of the cross-sectional variation in returns listed on the JSE. The results indicate that momentum on a univariate basis produces significantly positive excess returns across estimation and holding periods between three and twelve months consistent with the findings of Jegadeesh and Titman (1993, 2001). Additionally, the results add to the current body of literature in describing the univariate specific methodological effects of direct and indirect

transaction costs, weighting assumptions as well as the allowance for a gap between portfolio holding and estimation periods. The univariate tests further indicate that momentum on the JSE also displays reversal in holding periods in excess of one year, with extreme loser shares outperforming extreme winners over holding periods of 24 to 60 months. The results are therefore highly consistent with international and local literature and clearly answer the first aspect of the research question as momentum is most certainly significant and profitable on a univariate basis.

The question of whether momentum is independent is broached in Chapters Four and Five of this study, where momentum is first combined with non-momentum factor anomalies in bivariate sorts and then tested against combinations on the non-momentum factor anomalies in multivariate time-series regressions. The purpose of the bivariate sorts is to ascertain whether the simultaneous sorting on both momentum and the non-momentum factor anomaly effects the momentum premium. The test therefore considers two key aspects, namely independence and interaction. Independence implies that the combination of momentum and the non-momentum factor does not affect the momentum premium and therefore implies that momentum is independent of the said style as it is present across the specific style stratum on the JSE.

A secondary test that is a corollary to the independence test is the test of interaction between the momentum premium and the specific factor anomaly. A positive interaction between momentum and the said anomaly is evidence in favour of momentum being independent and exacerbated by the non-momentum factor, while a negative interaction still implies independence but points to the combination of the strategies being suboptimal. In the case of the interaction being negative to the point that it negates the momentum premium, this would imply that momentum is not independent of the said factor (as was seen in the bivariate sorts on value and momentum). The results presented in Chapter Four clearly indicate that momentum is largely independent on the JSE of the other non-momentum factor anomalies considered and further demonstrates the optimal and sub-optimal portfolio combination strategies. In fact, the findings of Chapter Four can be considered novel and easily the most in-depth South African study into the independence and interaction of momentum with other non-momentum factors.

A further significant contribution to the body of knowledge is the application of a dynamic weighting methodology that was developed in order to mitigate the effects of the inherent illiquid and small investment universe that is the JSE. The additional robustness provided by applying two sorting methodologies should become a standard tool for empirical studies that intend on conducting bivariate stylistic sorts on the JSE.

As mentioned in parentheses above, the only non-momentum factor that negated the momentum premium was value, proxied by the book-to-market ratio. The results of Chapter Four present a notable finding related to the complex covariance structure between momentum and value on the JSE. The topic was first considered by Asness (1997) and then by Fraser and Page (2000) where Asness (1997) asserted that the momentum effect is expected to maintain a negative relationship with the value premium as value shares should largely be loser shares while winner shares are typically growth shares. Fraser and Page (2000) considered the findings of Asness (1997) but found that the assertion of Asness (1997) did not apply on the cross-section of shares listed on the JSE.

This study found evidence consistent with both studies where on a long-only basis, momentum maintains a positive relationship with value while on an excess return basis, displays a significantly negative relationship with the value premium. The position of this study is best articulated by Asness *et al.* (2013). The reasoning behind the negative relationship is logical in that value and momentum are on opposite sides of the investment spectrum, where momentum is the application of investing in shares that produce positive recent performance while a value strategy implies investing in shares that have recently been oversold by the market to a point that they are trading at a discount to their accounting based intrinsic value. Fama and French (1996) confirmed the diametric position as they found that the value premium, proxied by the book-to-market ratio loads positively on extreme loser shares. The independent sort results of this study confirm these findings as the main cause of momentum producing poor excess returns in the value tercile is driven by the extremely positive performance of the extreme loser portfolio. Similarly, the poor performance of the value premium in the winner tercile is driven by the significantly positive performance of the high growth winner shares.

Chapter Five extended the testing of momentum to a parametric linear framework. The application of attribution time-series regressions is in effect a risk-based test that considers non-momentum styles as factor premiums. This study incorporated a series of robustness tests in testing whether the momentum premium is explained by the non-momentum factors considered. Firstly, three distinctive weighting methodologies where applied in estimating momentum quintile portfolios, namely equal, value and momentum rank or relative strength weighting. The benefit of applying three weighting methodologies is the additional robustness related to determining whether weighting mitigates or exacerbates the momentum effect on the JSE and illuminates the effect of weighting on risk-adjusted excess returns. The time-series regression analysis was further augmented by the application of the Gibbons, Ross and Shanken (1989) test statistic which determines whether the factors/risk premiums applied

within the regression analysis jointly explain the cross-sectional variation in momentum alphas. To the best of the authors' knowledge, this is the first time that GRS tests are applied to the study of momentum on the JSE and therefore provides a significant methodological contribution to the existing body of South African literature.

The robustness of the time-series analysis was further augmented by the number of attribution models applied. The time-series analysis in Chapter Five considered four distinctive attribution models, namely; the CAPM or market model, the Fama-French Three factor model, a five factor model that considered excess return on the JSE, the low beta anomaly, the low volatility anomaly, the liquidity premium and the currency risk premium. The final attribution model applied the APT factors of van Rensburg (2001) as the author found that the FINDI and RESI indices are the two key principal components that drive the cross-sectional variation in share returns on the JSE. In general, the international standard in terms of attribution models applied in literature is limited to the market model and Fama-French Three Factor model. The intention of this study was to incorporate as many factors as possible in attempt to describe the momentum effect on the JSE and when evaluated against to the current body of South African literature, the approach and findings are highly robust, novel and unique.

Most importantly, the findings of Chapter Five are consistent with international literature on the momentum premium, specifically Jegadeesh and Titman (1993, 2001) and Fama and French (1996). Irrespective of the weighting methodology and attribution model applied, the momentum effect cannot be explained by the considered factor premiums as portfolio alphas consistently decrease monotonically when moving from the extreme winner to loser quintile portfolio. The results were further confirmed by the results of the GRS tests where all strongly rejected the null of time-series alphas being jointly equal to zero. Furthermore, consistent with international literature, the application of a Fama-French attribution actually causes risk-adjusted returns to increase when compared to the market model. The findings in fact extend the evidence as it was found that the risk-adjusted momentum premium maintains a positive relationship with the number of non-momentum factors incorporated within an attribution model! The result manifested in portfolio alphas increasing given the number of non-momentum explanatory included within the respective attribution models.

A further finding relates to the relative contribution of the long and short positions in the respective winner and loser portfolios to the overall risk-adjusted excess return. The evidence presented is somewhat contrary to the findings of Lesmond *et al.* (2004). The authors found that the majority of momentum premium is due to the short position in the loser portfolio. The findings presented seem to only confirm the result when applying the CAPM as the attribution model. Uniquely, the results indicate that the findings of Lesmond *et al.* (2004) are sensitive

to the attribution model applied, as a distinctive shift was found when applying the latter three attribution models where momentum excess return alphas were largely driven by the long position in the respective winner portfolio. Such a finding may be unique to the JSE, however, it certainly creates avenues of future research into the mechanics of the momentum premium in developed and emerging markets.

Lastly, a consistent result emerged in relation to the weighting methodologies applied. Across all of the regression specifications, and therefore irrespective of the attribution model, market capitalization weighted momentum portfolios produced higher alphas than their equally weighted counterparts and both were superseded by the momentum rank weighted alphas. The result therefore clearly indicates that the weighted relative strength or momentum rank weighting methodology produces the highest levels of risk-adjusted return thereby significantly adding to the body of knowledge in terms of the effect of weighting on portfolio returns. The result is also of high importance to investors and practitioners as it clearly indicates that a relative strength application of a momentum strategy tends to achieve superior risk-adjusted returns when compared to simple equal and value weighting.

Considering the results of Chapters Three, Four and Five simultaneously, the evidence presented clearly depicts consistent proof in favour of momentum being profitable, significant and independent on the JSE. Chapter Six offers the logical extension to the study and is, in essence, the pen-ultimate test related to the research question of whether momentum is not only present, but 'priced' on the cross-section of shares listed on the JSE. Chapter Six therefore presents an extension to the work of van Rensburg and Robertson (2003), Basiewicz and Auret (2010) and Gilbert *et al.* (2011) in attempting to describe the priced factors that explain the cross-sectional variation in share returns on the JSE. Importantly, Chapter Six deviates from the conventionally applied Fama-Macbeth methodology in favour of panel data regressions. The reason for the deviation is largely related to the number of 'pricing' factors considered and the relatively limited number of liquid and tradeable shares listed on the JSE. The benefit of the share-by-share panel aggregation methodology is that it allows for the application various econometric models that account for time-series and cross sectional heterogeneity while simultaneously allowing for the evaluation of multiple pricing factors.

The results of the panel data regressions provide evidence that is highly consistent with the findings of Chapters Three to Five as, irrespective of the econometric model applied, the momentum premium is highly significant and present on the JSE, irrespective of the other pricing factors considered. The implication of the result is far reaching in that Chapter Six confirms that the recent cumulative historical return of a share is a significant predictor of expected future returns. Furthermore, the evidence presented confirms the findings of

Chapters Four and Five as the momentum factor is a consistently significant explanatory variable when applied in tandem with the other non-momentum factors. The results of Chapter Six are probably the most far reaching as they effectively dictate that any pricing model applied to shares on the JSE, be it for the purpose of fund attribution, valuation or risk appraisal requires the incorporation of a momentum factor and that the exclusion of a momentum factor would amount to model misspecification. Furthermore (and indirectly), Chapter Six describes a parsimonious, JSE specific pricing model that confirms the findings of Basiewicz and Auret (2010) but augments the three factor model to a five factor model that includes momentum and the low beta premium as priced factors that explain the cross-sectional variation in share returns listed on the JSE.

This study has largely avoided the question of what drives momentum on the JSE. As described in the opening paragraphs of this chapter, the approach applied in this study has maintained that the lack of an *a priori* risk-based explanation does not preclude a factor from being priced and thereby contributing to or explaining the cross-sectional variation in share returns on the JSE. However, it should be noted that the analysis conducted in Chapters Four and Five conform to the typical risk-based tests found in literature. Firstly, typical risk proxies such as the market risk premium, size and value premium, excess returns on the FINDI and RESI, liquidity and other factor anomalies (low beta, low volatility and currency risk) fail to describe the momentum premium via non-parametric unconditional bivariate sorts and conditional parametric time-series regression attribution analysis. Secondly, Chapter Three clearly displays that the momentum premium on the JSE does eventually reverse as historical losers outperform historical winners over holding periods in excess of 24 months which is highly consistent with behavioural explanations of momentum such as herding and self-attribution bias.

When viewing the results of Chapters Three to Five in conjunction, one could easily conclude that a risk-based explanation of momentum on the JSE is implausible and therefore, fail to reject the hypothesis of momentum being driven by behavioural biases. However, considering the results of Chapter Six, the evidence presented clearly indicates that momentum is a priced factor on the JSE, implying that momentum contributes to the cross-sectional variation in share returns and is both independent and significant. The latter finding therefore justifies the applied theoretical framework applied in this study in that even though there is no clear risk-based justification for momentum, the momentum premium is significant, independent of other risk factors and contributes to the cross-sectional variation in share returns and therefore, is a priced factor.

Lastly, like the studies conducted by van Rensburg and Robertson (2003), Auret and Sinclaire (2006), Basiewicz and Auret (2009, 2010), Auret and Kline (2010), Gilbert *et al.* (2011) and Page and Britten (2013), the findings of this study clearly articulate the inefficiency of the CAPM in explaining the cross-sectional variation of returns on the JSE. The results of Chapter Five indicate that the equity market risk premium cannot explain momentum on the JSE while Chapter Six clearly describes that additional factors are required to adequately describe the cross-sectional variation in share returns on the JSE. A corollary finding to the in-depth study conducted on momentum on the JSE is that a feasible and parsimonious factor model on the JSE should take the form of an augmented Carhart (1997) model that includes a 'Betting Against Beta' factor per Frazzini and Pedersen (2013). Such a finding is a significant addition to the current body of JSE specific financial economics and asset pricing literature and offers an obvious avenue of future research where such a model would be tested against other pricing models in order to determine whether the said model explains a greater proportion of the cross-sectional variation in returns of a multiple number of assets and indices including JSE sector specific indices, mutual funds, unit trusts and any other type of equity based investment instruments.

In conclusion, when considering the key research agenda of this study, specifically whether momentum is a priced factor on the JSE, the results are conclusive. In univariate tests, the momentum premium is clearly significant and although sensitive to methodological variations, is consistent in providing both gross and risk-adjusted profits. In multivariate tests, the momentum effect has proven to be both significant and independent of other non-momentum factor proxies and investment styles, implying that momentum is a unique factor premium. Lastly, and most importantly, the final multivariate test applies momentum as a dependent variable in conjunction with other non-momentum factor premiums. The results of the final test are both clear and precise in answering the key research question posed, as momentum, when combined with other factor proxies, definitively and independently describes the cross-sectional variation in share returns on the JSE. Therefore, the results of this study eloquently describe that momentum in share prices is present, profitable, independent and priced on the cross-section of shares listed on the JSE.

7.3 Limitations and Recommendations for Future Research

The limitations of this study were partially described in Chapter One and deserve both reiteration and expansion. Firstly, a significant limitation of this study relates to the data being confined to the JSE or geographically to South Africa whereas an African wide study of

momentum would significantly contribute to the body of knowledge related to asset pricing, investment styles and factor anomalies on a developing market and African basis.

A secondary significant limitation relates to the data set used. Findata@Wits consists of data over the period January 1989 to June 2015, making it one of the most extensive South African specific equity databases available. However, the database is relatively short in terms of time-series and narrow in terms of cross-section when compared to other international databases such as the CRSP, which contains data on the cross-section of shares listed on the NYSE, AMEX and NASDAQ over the period January 1926 to June 2016. An obvious further limitation of the study is that the data are limited to share prices, while many momentum studies have been conducted on other non-equity traded assets such as commodities, bonds, stock indices, futures and other derivative instruments.

Probably the most significant limitation of this study is that it takes no distinct stand on what drives momentum on the JSE. Indirectly, the study conducts all the necessary tests found in typical risk based momentum literature, however, no direct conclusion is drawn in relation to whether momentum is an unspecified risk proxy or behavioral anomaly. As articulated across the study, the key research question centers on whether momentum is priced, yet, the specific determination of what drives momentum on the JSE would add significantly to the South African and developing market body of literature, specifically in relation to the study of market anomalies and relatively unexplored Afrocentric behavioral finance.

The limitations described above can be directly linked to recommendations for further research specifically related to the study of momentum. The current body of knowledge would significantly benefit from a continental exploration of momentum, like the studies conducted by Rouwenhorst (1998, 1999) where other African indices and their share constituents can be considered in order to determine whether there is an African momentum premium, potentially proving that African markets are integrated, providing evidence in favor of momentum being a priced factor on the African continent. A further avenue of momentum related research could be the extension of analysis to other traded assets such as commodities traded on the SAFEX (South African futures exchange) or government and corporate debt (traded on the JSE, previously known as BESA).

Probably the most important unexplored avenue of future research is the investigation of what drives momentum on the JSE, or more specifically, determining whether momentum on the JSE compensation for an ‘unspecified risk’ or a behavioral anomaly. The determination of whether momentum is driven by risk would require the application of all of the risk-based tests applied in literature in order to determine whether momentum is driven by risk on the JSE.

Importantly, the lack of consistent (empirical) risk-based proof of momentum on the JSE would not automatically imply that momentum is a behavioral anomaly. Additional testing would be required, where using fundamental inputs related to the JSE, simulation analysis applying the theoretical behavioral models described by Barberis *et al.* (1998) and Daniel *et al.* (1998) should be conducted in order to determine whether internationally accepted behavioral models are able to generate momentum profits similar to those found in South African literature.

In conclusion, the distinctive benefit of this study is not limited to its substantial contribution to the current body of knowledge related to momentum, factor anomalies and asset pricing on the JSE. As articulated above, the study provides a series of avenues for further research that would significantly enrich both local and international knowledge on momentum, asset pricing and behavioral finance in developing markets and on the African continent.

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APPENDICES

Appendix 1a: Time-Series Regression Sample Statistics

Equally Weighted Momentum Portfolio Summary Statistics

	EW1	EW2	EW3	EW4	EW5
Mean	0.008596	0.001993	-0.000149	-0.001759	-0.006683
Median	0.011830	0.004470	0.003606	0.004654	-0.010494
Maximum	0.140251	0.115786	0.101959	0.118042	0.150331
Minimum	-0.409466	-0.295345	-0.292304	-0.254586	-0.247654
Std. Dev.	0.061491	0.048504	0.050331	0.051452	0.054262
Skewness	-1.859982	-1.224209	-1.224476	-1.020331	-0.325608
Kurtosis	12.53793	8.700065	7.585733	5.670626	4.230121
Jarque-Bera	982.5952	360.8015	253.3717	105.9051	18.16200
Probability	0.000000	0.000000	0.000000	0.000000	0.000114
Sum	1.933991	0.448360	-0.033492	-0.395675	-1.503744
Sum Sq. Dev.	0.846972	0.526994	0.567435	0.592986	0.659536
Observations	225	225	225	225	225

Market Capitalization Weighted Momentum Portfolio Summary Statistics

	MCW1	MCW2	MCW3	MCW4	MCW5
Mean	0.009548	0.002493	0.000551	-0.001212	-0.006454
Median	0.016449	0.004970	0.006042	0.004388	-0.009555
Maximum	0.138705	0.118862	0.094930	0.125926	0.166240
Minimum	-0.411766	-0.301149	-0.293180	-0.255062	-0.257395
Std. Dev.	0.062082	0.048473	0.050302	0.052189	0.055346
Skewness	-1.867113	-1.224642	-1.232545	-0.984666	-0.307176
Kurtosis	12.54193	9.116362	7.677376	5.535918	4.441966
Jarque-Bera	984.3089	406.9583	262.0735	96.64828	23.03152
Probability	0.000000	0.000000	0.000000	0.000000	0.000010
Sum	2.148341	0.560864	0.124037	-0.272793	-1.452236
Sum Sq. Dev.	0.863344	0.526314	0.566788	0.610110	0.686153
Observations	225	225	225	225	225

Momentum Rank Weighted Momentum Portfolio Summary Statistics

	MMW1	MMW2	MMW3	MMW4	MMW5
Mean	0.010011	0.001747	-0.000240	-0.001805	-0.007055
Median	0.020096	0.005396	0.003949	0.005509	-0.010943
Maximum	0.293258	0.116780	0.100109	0.119870	0.153494
Minimum	-0.447058	-0.298465	-0.290560	-0.252652	-0.244688
Std. Dev.	0.091500	0.048680	0.050180	0.051613	0.054585
Skewness	-0.692916	-1.262542	-1.225983	-0.996800	-0.277269
Kurtosis	6.483419	8.935790	7.554614	5.568565	4.138678
Jarque-Bera	131.7631	390.0905	250.8435	99.11216	15.03842
Probability	0.000000	0.000000	0.000000	0.000000	0.000543
Sum	2.252377	0.393106	-0.053925	-0.406210	-1.587442
Sum Sq. Dev.	1.875383	0.530818	0.564046	0.596724	0.667403
Observations	225	225	225	225	225

Group Unit Root Tests across Momentum Sorted Portfolios

Group unit root test: Summary
Series: EW1, EW2, EW3, EW4, EW5, MCW1, MCW2, MCW3, MCW4, MCW5, MMW1, MMW2, MMW3, MMW4, MMW5
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-54.9433	0.0000	15	3360
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-48.0040	0.0000	15	3360
ADF - Fisher Chi-square	1401.94	0.0000	15	3360
PP - Fisher Chi-square	1398.25	0.0000	15	3360

** Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.

Summary Statistics of Time-Series Excess Returns for Independent Variables Applied in Attribution Regressions

	EMRP	BETA	FINDIETR	HLMLL	IDIO	RTMRH	SMB	VMG
Mean	0.003926	0.005532	0.013203	0.003540	0.011400	0.003314	-0.003223	0.005770
Median	0.005261	0.010019	0.016220	0.002161	0.010621	0.001539	0.000725	0.006162
Maximum	0.130294	0.160186	0.165747	0.159713	0.140968	0.185998	0.118332	0.151561
Minimum	-0.309375	-0.194751	-0.316350	-0.137435	-0.158174	-0.174690	-0.193010	-0.158064
Std. Dev.	0.056235	0.059155	0.055636	0.043926	0.045828	0.047404	0.047912	0.043007
Skewness	-0.837019	-0.359383	-1.028485	0.165838	0.164003	0.148025	-0.602323	-0.166643
Kurtosis	6.610875	3.901591	7.921474	3.876960	4.069989	4.463889	4.197669	5.042154
Jarque-Bera	147.8477	12.40858	265.5524	8.204634	11.68967	20.81908	26.93209	39.96042
Probability	0.000000	0.002021	0.000000	0.016534	0.002895	0.000030	0.000001	0.000000
Sum	0.879478	1.239207	2.957418	0.792937	2.553605	0.742385	-0.722063	1.292493
Sum Sq.Dev.	0.705218	0.780356	0.690268	0.430272	0.468355	0.501112	0.511906	0.412462
Observations	224	224	224	224	224	224	224	224

Group Unit Root test for Independent Variables applied in Time-series Regression Analysis

Group unit root test: Summary
Series: EMRP, BETA, FINDIETR, HLMLL, IDIO, RTMRH, SMB, VMG__EW_
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-46.1192	0.0000	8	1784
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-41.1002	0.0000	8	1784
ADF - Fisher Chi-square	858.101	0.0000	8	1784
PP - Fisher Chi-square	859.401	0.0000	8	1784

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Appendix 1b: Time Series Regression Output – Market Model Regressions

Dependent Variable: EW1
Method: Least Squares
Sample: 1997M01 2015M09
Included observations: 225

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMRP	0.858201	0.045636	18.80530	0.0000
C	0.005250	0.002561	2.049831	0.0416

R-squared	0.613277	Mean dependent var	0.008596
Adjusted R-squared	0.611542	S.D. dependent var	0.061491
S.E. of regression	0.038325	Akaike info criterion	-3.676579
Sum squared resid	0.327544	Schwarz criterion	-3.646213
Log likelihood	415.6151	Hannan-Quinn criter.	-3.664323
F-statistic	353.6394	Durbin-Watson stat	1.642860
Prob(F-statistic)	0.000000		

Dependent Variable: EW2
Method: Least Squares
Sample: 1997M01 2015M09
Included observations: 225

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMRP	0.657167	0.037606	17.47512	0.0000
C	-0.000569	0.002111	-0.269660	0.7877

R-squared	0.577955	Mean dependent var	0.001993
Adjusted R-squared	0.576062	S.D. dependent var	0.048504
S.E. of regression	0.031581	Akaike info criterion	-4.063656
Sum squared resid	0.222415	Schwarz criterion	-4.033290
Log likelihood	459.1613	Hannan-Quinn criter.	-4.051400
F-statistic	305.3798	Durbin-Watson stat	1.650371
Prob(F-statistic)	0.000000		

Dependent Variable: EW3
Method: Least Squares
Sample: 1997M01 2015M09
Included observations: 225

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMRP	0.700734	0.037497	18.68755	0.0000
C	-0.002881	0.002104	-1.368790	0.1724

R-squared	0.610293	Mean dependent var	-0.000149
Adjusted R-squared	0.608545	S.D. dependent var	0.050331
S.E. of regression	0.031490	Akaike info criterion	-4.069434
Sum squared resid	0.221134	Schwarz criterion	-4.039069
Log likelihood	459.8113	Hannan-Quinn criter.	-4.057179
F-statistic	349.2243	Durbin-Watson stat	1.673909
Prob(F-statistic)	0.000000		

Dependent Variable: EW4
Method: Least Squares
Sample: 1997M01 2015M09
Included observations: 225

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMRP	0.668614	0.042021	15.91146	0.0000
C	-0.004365	0.002358	-1.850916	0.0655

R-squared	0.531684	Mean dependent var	-0.001759
Adjusted R-squared	0.529584	S.D. dependent var	0.051452
S.E. of regression	0.035289	Akaike info criterion	-3.841643
Sum squared resid	0.277705	Schwarz criterion	-3.811278
Log likelihood	434.1849	Hannan-Quinn criter.	-3.829388
F-statistic	253.1746	Durbin-Watson stat	1.476227
Prob(F-statistic)	0.000000		

Dependent Variable: EW5
Method: Least Squares
Sample: 1997M01 2015M09
Included observations: 225

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMRP	0.724224	0.042914	16.87634	0.0000
C	-0.009507	0.002408	-3.947258	0.0001

R-squared	0.560860	Mean dependent var	-0.006683
Adjusted R-squared	0.558891	S.D. dependent var	0.054262
S.E. of regression	0.036039	Akaike info criterion	-3.799602
Sum squared resid	0.289629	Schwarz criterion	-3.769236
Log likelihood	429.4552	Hannan-Quinn criter.	-3.787346
F-statistic	284.8110	Durbin-Watson stat	1.664360
Prob(F-statistic)	0.000000		

Dependent Variable: EWML
Method: Least Squares
Sample: 1997M01 2015M09
Included observations: 225
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMRP	0.133977	0.093382	1.434725	0.1528
C	0.014757	0.003613	4.084144	0.0001

R-squared	0.024510	Mean dependent var	0.015279
Adjusted R-squared	0.020135	S.D. dependent var	0.048019
S.E. of regression	0.047533	Akaike info criterion	-3.245949
Sum squared resid	0.503836	Schwarz criterion	-3.215584
Log likelihood	367.1693	Hannan-Quinn criter.	-3.233694
F-statistic	5.603026	Durbin-Watson stat	1.835673
Prob(F-statistic)	0.018785		

Dependent Variable: MCW1
Method: Least Squares
Sample: 1997M01 2015M09
Included observations: 225

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMRP	0.885756	0.044399	19.94998	0.0000
C	0.006095	0.002492	2.446168	0.0152

R-squared	0.640903	Mean dependent var	0.009548
Adjusted R-squared	0.639292	S.D. dependent var	0.062082
S.E. of regression	0.037286	Akaike info criterion	-3.731549
Sum squared resid	0.310025	Schwarz criterion	-3.701184
Log likelihood	421.7993	Hannan-Quinn criter.	-3.719293
F-statistic	398.0016	Durbin-Watson stat	1.691081
Prob(F-statistic)	0.000000		

Dependent Variable: MCW2
Method: Least Squares
Sample: 1997M01 2015M09
Included observations: 225
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMRP	0.678334	0.049288	13.76255	0.0000
C	-0.000152	0.002430	-0.062399	0.9503

R-squared	0.616581	Mean dependent var	0.002493
Adjusted R-squared	0.614861	S.D. dependent var	0.048473
S.E. of regression	0.030082	Akaike info criterion	-4.160930
Sum squared resid	0.201799	Schwarz criterion	-4.130565
Log likelihood	470.1046	Hannan-Quinn criter.	-4.148674
F-statistic	358.6089	Durbin-Watson stat	1.691306
Prob(F-statistic)	0.000000		

Dependent Variable: MCW3
Method: Least Squares
Sample: 1997M01 2015M09
Included observations: 225

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMRP	0.724162	0.035387	20.46402	0.0000
C	-0.002272	0.001986	-1.143872	0.2539

R-squared	0.652527	Mean dependent var	0.000551
Adjusted R-squared	0.650969	S.D. dependent var	0.050302
S.E. of regression	0.029718	Akaike info criterion	-4.185282
Sum squared resid	0.196944	Schwarz criterion	-4.154917
Log likelihood	472.8443	Hannan-Quinn criter.	-4.173027
F-statistic	418.7759	Durbin-Watson stat	1.647235
Prob(F-statistic)	0.000000		

Dependent Variable: MCW4
Method: Least Squares
Sample: 1997M01 2015M09
Included observations: 225

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMRP	0.694408	0.041436	16.75840	0.0000
C	-0.003919	0.002325	-1.685414	0.0933

R-squared	0.557403	Mean dependent var	-0.001212
Adjusted R-squared	0.555418	S.D. dependent var	0.052189
S.E. of regression	0.034798	Akaike info criterion	-3.869657
Sum squared resid	0.270033	Schwarz criterion	-3.839291
Log likelihood	437.3364	Hannan-Quinn criter.	-3.857401
F-statistic	280.8440	Durbin-Watson stat	1.516487
Prob(F-statistic)	0.000000		

Dependent Variable: MCW5
Method: Least Squares
Sample: 1997M01 2015M09
Included observations: 225
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMRP	0.751760	0.045065	16.68175	0.0000
C	-0.009385	0.002745	-3.418571	0.0007

R-squared	0.580878	Mean dependent var	-0.006454
Adjusted R-squared	0.578999	S.D. dependent var	0.055346
S.E. of regression	0.035911	Akaike info criterion	-3.806695
Sum squared resid	0.287581	Schwarz criterion	-3.776330
Log likelihood	430.2532	Hannan-Quinn criter.	-3.794440
F-statistic	309.0653	Durbin-Watson stat	1.664118
Prob(F-statistic)	0.000000		

Dependent Variable: MCWML
Method: Least Squares
Sample: 1997M01 2015M09
Included observations: 225
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMRP	0.133996	0.096796	1.384323	0.1676
C	0.015480	0.003758	4.119050	0.0001

R-squared	0.022826	Mean dependent var	0.016003
Adjusted R-squared	0.018444	S.D. dependent var	0.049766
S.E. of regression	0.049304	Akaike info criterion	-3.172754
Sum squared resid	0.542098	Schwarz criterion	-3.142389
Log likelihood	358.9349	Hannan-Quinn criter.	-3.160499
F-statistic	5.209079	Durbin-Watson stat	1.823875
Prob(F-statistic)	0.023412		

Dependent Variable: MMW1
Method: Least Squares
Sample: 1997M01 2015M09
Included observations: 225

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMRP	0.953859	0.088569	10.76973	0.0000
C	0.006292	0.004971	1.265861	0.2069

R-squared	0.342158	Mean dependent var	0.010011
Adjusted R-squared	0.339208	S.D. dependent var	0.091500
S.E. of regression	0.074380	Akaike info criterion	-2.350423
Sum squared resid	1.233706	Schwarz criterion	-2.320057
Log likelihood	266.4226	Hannan-Quinn criter.	-2.338167
F-statistic	115.9870	Durbin-Watson stat	1.845340
Prob(F-statistic)	0.000000		

Dependent Variable: MMW2
Method: Least Squares
Sample: 1997M01 2015M09
Included observations: 225

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMRP	0.654413	0.038141	17.15784	0.0000
C	-0.000804	0.002141	-0.375586	0.7076

R-squared	0.568992	Mean dependent var	0.001747
Adjusted R-squared	0.567059	S.D. dependent var	0.048680
S.E. of regression	0.032030	Akaike info criterion	-4.035410
Sum squared resid	0.228787	Schwarz criterion	-4.005045
Log likelihood	455.9836	Hannan-Quinn criter.	-4.023155
F-statistic	294.3914	Durbin-Watson stat	1.660578
Prob(F-statistic)	0.000000		

Dependent Variable: MMW3
Method: Least Squares
Sample: 1997M01 2015M09
Included observations: 225
HAC standard errors & covariance (Prewhitening with lags = 2 from AIC maxlags = 6, Bartlett kernel, Integer Newey-West fixed bandwidth = 5.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMRP	0.695546	0.055474	12.53827	0.0000
C	-0.002951	0.002500	-1.180372	0.2391

R-squared	0.604901	Mean dependent var	-0.000240
Adjusted R-squared	0.603129	S.D. dependent var	0.050180
S.E. of regression	0.031612	Akaike info criterion	-4.061683
Sum squared resid	0.222854	Schwarz criterion	-4.031317
Log likelihood	458.9393	Hannan-Quinn criter.	-4.049427
F-statistic	341.4151	Durbin-Watson stat	1.687150
Prob(F-statistic)	0.000000		

Dependent Variable: MMW4
Method: Least Squares
Sample: 1997M01 2015M09
Included observations: 225
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMRP	0.671476	0.052878	12.69861	0.0000
C	-0.004423	0.002973	-1.487641	0.1383

R-squared	0.532887	Mean dependent var	-0.001805
Adjusted R-squared	0.530792	S.D. dependent var	0.051613
S.E. of regression	0.035355	Akaike info criterion	-3.837930
Sum squared resid	0.278738	Schwarz criterion	-3.807564
Log likelihood	433.7671	Hannan-Quinn criter.	-3.825674
F-statistic	254.4003	Durbin-Watson stat	1.472014
Prob(F-statistic)	0.000000		

Dependent Variable: MMW5
Method: Least Squares
Sample: 1997M01 2015M09
Included observations: 225

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMRP	0.726674	0.043309	16.77888	0.0000
C	-0.009888	0.002431	-4.068205	0.0001

R-squared	0.558005	Mean dependent var	-0.007055
Adjusted R-squared	0.556023	S.D. dependent var	0.054585
S.E. of regression	0.036371	Akaike info criterion	-3.781264
Sum squared resid	0.294989	Schwarz criterion	-3.750898
Log likelihood	427.3922	Hannan-Quinn criter.	-3.769008
F-statistic	281.5307	Durbin-Watson stat	1.668471
Prob(F-statistic)	0.000000		

Dependent Variable: MMWML
Method: Least Squares
Sample: 1997M01 2015M09
Included observations: 225

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMRP	0.227186	0.094616	2.401125	0.0172
C	0.016180	0.005310	3.047091	0.0026

R-squared	0.025202	Mean dependent var	0.017066
Adjusted R-squared	0.020831	S.D. dependent var	0.080299
S.E. of regression	0.079458	Akaike info criterion	-2.218315
Sum squared resid	1.407943	Schwarz criterion	-2.187950
Log likelihood	251.5605	Hannan-Quinn criter.	-2.206060
F-statistic	5.765402	Durbin-Watson stat	1.836858
Prob(F-statistic)	0.017165		

Appendix 1c: Time Series Regression Output – Fama-French Regressions

Dependent Variable: EW1
Method: Least Squares
Sample: 1 225
Included observations: 225
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMRP	1.105668	0.081569	13.55503	0.0000
SMB	0.561871	0.061513	9.134201	0.0000
VMG__EW_	-0.095479	0.058060	-1.644496	0.1015
C	0.006647	0.002049	3.244479	0.0014

R-squared	0.744177	Mean dependent var	0.008596
Adjusted R-squared	0.740704	S.D. dependent var	0.061491
S.E. of regression	0.031312	Akaike info criterion	-4.072024
Sum squared resid	0.216675	Schwarz criterion	-4.011293
Log likelihood	462.1027	Hannan-Quinn criter.	-4.047512
F-statistic	214.2924	Durbin-Watson stat	2.028479
Prob(F-statistic)	0.000000		

Dependent Variable: EW2
Method: Least Squares
Sample: 1 225
Included observations: 225
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMRP	0.829122	0.054948	15.08912	0.0000
SMB	0.401597	0.049597	8.097241	0.0000
VMG__EW_	-0.111670	0.045667	-2.445287	0.0153
C	0.000699	0.001830	0.382136	0.7027

R-squared	0.686867	Mean dependent var	0.001993
Adjusted R-squared	0.682616	S.D. dependent var	0.048504
S.E. of regression	0.027326	Akaike info criterion	-4.344362
Sum squared resid	0.165019	Schwarz criterion	-4.283631
Log likelihood	492.7407	Hannan-Quinn criter.	-4.319851
F-statistic	161.5902	Durbin-Watson stat	2.006689
Prob(F-statistic)	0.000000		

Dependent Variable: EW3
Method: Least Squares
Sample: 1 225
Included observations: 225
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMRP	0.862358	0.047291	18.23513	0.0000
SMB	0.348266	0.057250	6.083214	0.0000
VMG__EW_	0.013472	0.048915	0.275417	0.7833
C	-0.002466	0.001976	-1.247511	0.2135

R-squared	0.689121	Mean dependent var	-0.000149
Adjusted R-squared	0.684901	S.D. dependent var	0.050331
S.E. of regression	0.028253	Akaike info criterion	-4.277647
Sum squared resid	0.176404	Schwarz criterion	-4.216917
Log likelihood	485.2353	Hannan-Quinn criter.	-4.253136
F-statistic	163.2956	Durbin-Watson stat	1.855573
Prob(F-statistic)	0.000000		

Dependent Variable: EW4
Method: Least Squares
Sample: 1 225
Included observations: 225

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMRP	0.837936	0.045405	18.45489	0.0000
SMB	0.376306	0.054149	6.949413	0.0000
VMG__EW_	-0.032329	0.051357	-0.629494	0.5297
C	-0.003626	0.002171	-1.669591	0.0964

R-squared	0.616232	Mean dependent var	-0.001759
Adjusted R-squared	0.611023	S.D. dependent var	0.051452
S.E. of regression	0.032089	Akaike info criterion	-4.022970
Sum squared resid	0.227569	Schwarz criterion	-3.962240
Log likelihood	456.5842	Hannan-Quinn criter.	-3.998459
F-statistic	118.2897	Durbin-Watson stat	1.579533
Prob(F-statistic)	0.000000		

Dependent Variable: EW5
Method: Least Squares
Sample: 1 225
Included observations: 225

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMRP	0.886179	0.046940	18.87907	0.0000
SMB	0.362989	0.055980	6.484240	0.0000
VMG__EW_	-0.043311	0.053094	-0.815746	0.4155
C	-0.008718	0.002245	-3.883385	0.0001

R-squared	0.631228	Mean dependent var	-0.006683
Adjusted R-squared	0.626222	S.D. dependent var	0.054262
S.E. of regression	0.033174	Akaike info criterion	-3.956463
Sum squared resid	0.243218	Schwarz criterion	-3.895732
Log likelihood	449.1021	Hannan-Quinn criter.	-3.931952
F-statistic	126.0954	Durbin-Watson stat	1.764425
Prob(F-statistic)	0.000000		

Dependent Variable: EWWML
Method: Least Squares
Sample: 1 225
Included observations: 225
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMRP	0.219489	0.105787	2.074819	0.0392
SMB	0.198882	0.100530	1.978329	0.0491
VMG__EW_	-0.052168	0.105532	-0.494332	0.6216
C	0.015365	0.003340	4.600755	0.0000

R-squared	0.051666	Mean dependent var	0.015279
Adjusted R-squared	0.038793	S.D. dependent var	0.048019
S.E. of regression	0.047078	Akaike info criterion	-3.256405
Sum squared resid	0.489810	Schwarz criterion	-3.195674
Log likelihood	370.3455	Hannan-Quinn criter.	-3.231894
F-statistic	4.013436	Durbin-Watson stat	1.875612
Prob(F-statistic)	0.008290		

Dependent Variable: MCW1
Method: Least Squares
Sample: 1 225
Included observations: 225
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMRP	1.107395	0.081410	13.60265	0.0000
SMB	0.504783	0.064644	7.808670	0.0000
VMG__EW_	-0.091826	0.058269	-1.575883	0.1165
C	0.007388	0.002059	3.588970	0.0004

R-squared	0.744567	Mean dependent var	0.009548
Adjusted R-squared	0.741099	S.D. dependent var	0.062082
S.E. of regression	0.031589	Akaike info criterion	-4.054404
Sum squared resid	0.220527	Schwarz criterion	-3.993673
Log likelihood	460.1205	Hannan-Quinn criter.	-4.029893
F-statistic	214.7324	Durbin-Watson stat	2.046026
Prob(F-statistic)	0.000000		

Dependent Variable: MCW2
Method: Least Squares
Sample: 1 225
Included observations: 225
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMRP	0.825681	0.054212	15.23064	0.0000
SMB	0.349623	0.048342	7.232286	0.0000
VMG__EW_	-0.117980	0.045849	-2.573229	0.0107
C	0.001082	0.001785	0.605887	0.5452

R-squared	0.700764	Mean dependent var	0.002493
Adjusted R-squared	0.696702	S.D. dependent var	0.048473
S.E. of regression	0.026695	Akaike info criterion	-4.391049
Sum squared resid	0.157492	Schwarz criterion	-4.330318
Log likelihood	497.9930	Hannan-Quinn criter.	-4.366538
F-statistic	172.5159	Durbin-Watson stat	2.010714
Prob(F-statistic)	0.000000		

Dependent Variable: MCW3
Method: Least Squares
Sample: 1 225
Included observations: 225
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMRP	0.867891	0.046529	18.65269	0.0000
SMB	0.311506	0.054644	5.700618	0.0000
VMG__EW_	0.004681	0.048777	0.095971	0.9236
C	-0.001855	0.001885	-0.984011	0.3262

R-squared	0.715020	Mean dependent var	0.000551
Adjusted R-squared	0.711152	S.D. dependent var	0.050302
S.E. of regression	0.027035	Akaike info criterion	-4.365774
Sum squared resid	0.161523	Schwarz criterion	-4.305043
Log likelihood	495.1496	Hannan-Quinn criter.	-4.341263
F-statistic	184.8312	Durbin-Watson stat	1.818861
Prob(F-statistic)	0.000000		

Dependent Variable: MCW4
Method: Least Squares
Sample: 1 225
Included observations: 225
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMRP	0.843654	0.067919	12.42140	0.0000
SMB	0.332436	0.067755	4.906403	0.0000
VMG__EW_	-0.031526	0.074880	-0.421024	0.6741
C	-0.003248	0.002517	-1.290401	0.1983

R-squared	0.621430	Mean dependent var	-0.001212
Adjusted R-squared	0.616291	S.D. dependent var	0.052189
S.E. of regression	0.032328	Akaike info criterion	-4.008139
Sum squared resid	0.230969	Schwarz criterion	-3.947408
Log likelihood	454.9156	Hannan-Quinn criter.	-3.983627
F-statistic	120.9253	Durbin-Watson stat	1.614398
Prob(F-statistic)	0.000000		

Dependent Variable: MCW5
Method: Least Squares
Sample: 1 225
Included observations: 225
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMRP	0.888296	0.051244	17.33480	0.0000
SMB	0.308695	0.061346	5.032045	0.0000
VMG__EW_	-0.047376	0.069909	-0.677681	0.4987
C	-0.008649	0.002575	-3.358386	0.0009

R-squared	0.629667	Mean dependent var	-0.006454
Adjusted R-squared	0.624639	S.D. dependent var	0.055346
S.E. of regression	0.033909	Akaike info criterion	-3.912675
Sum squared resid	0.254105	Schwarz criterion	-3.851944
Log likelihood	444.1759	Hannan-Quinn criter.	-3.888163
F-statistic	125.2532	Durbin-Watson stat	1.739329
Prob(F-statistic)	0.000000		

Dependent Variable: MCWWML
Method: Least Squares
Sample: 1 225
Included observations: 225
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMRP	0.219099	0.108591	2.017650	0.0448
SMB	0.196088	0.106367	1.843509	0.0666
VMG__EW_	-0.044450	0.112422	-0.395382	0.6929
C	0.016037	0.003448	4.650673	0.0000

R-squared	0.047256	Mean dependent var	0.016003
Adjusted R-squared	0.034322	S.D. dependent var	0.049766
S.E. of regression	0.048904	Akaike info criterion	-3.180295
Sum squared resid	0.528545	Schwarz criterion	-3.119564
Log likelihood	361.7832	Hannan-Quinn criter.	-3.155784
F-statistic	3.653830	Durbin-Watson stat	1.860704
Prob(F-statistic)	0.013326		

Dependent Variable: MMW1
Method: Least Squares
Sample: 1 225
Included observations: 225
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMRP	1.289269	0.122550	10.52038	0.0000
SMB	0.776792	0.122456	6.343418	0.0000
VMG__EW_	-0.191248	0.112111	-1.705882	0.0894
C	0.008592	0.004507	1.906485	0.0579

R-squared	0.455901	Mean dependent var	0.010011
Adjusted R-squared	0.448515	S.D. dependent var	0.091500
S.E. of regression	0.067950	Akaike info criterion	-2.522479
Sum squared resid	1.020394	Schwarz criterion	-2.461749
Log likelihood	287.7789	Hannan-Quinn criter.	-2.497968
F-statistic	61.72539	Durbin-Watson stat	2.155658
Prob(F-statistic)	0.000000		

Dependent Variable: MMW2
Method: Least Squares
Sample: 1 225
Included observations: 225
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMRP	0.827175	0.056745	14.57704	0.0000
SMB	0.401853	0.049662	8.091710	0.0000
VMG__EW_	-0.105588	0.046105	-2.290182	0.0230
C	0.000427	0.001890	0.226052	0.8214

R-squared	0.676881	Mean dependent var	0.001747
Adjusted R-squared	0.672494	S.D. dependent var	0.048680
S.E. of regression	0.027859	Akaike info criterion	-4.305738
Sum squared resid	0.171517	Schwarz criterion	-4.245007
Log likelihood	488.3955	Hannan-Quinn criter.	-4.281227
F-statistic	154.3193	Durbin-Watson stat	1.990603
Prob(F-statistic)	0.000000		

Dependent Variable: MMW3
Method: Least Squares
Sample: 1 225
Included observations: 225
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMRP	0.856505	0.047596	17.99549	0.0000
SMB	0.348535	0.057045	6.109868	0.0000
VMG__EW_	0.006520	0.050073	0.130206	0.8965
C	-0.002493	0.001979	-1.259390	0.2092

R-squared	0.683634	Mean dependent var	-0.000240
Adjusted R-squared	0.679340	S.D. dependent var	0.050180
S.E. of regression	0.028416	Akaike info criterion	-4.266143
Sum squared resid	0.178445	Schwarz criterion	-4.205413
Log likelihood	483.9411	Hannan-Quinn criter.	-4.241632
F-statistic	159.1863	Durbin-Watson stat	1.864019
Prob(F-statistic)	0.000000		

Dependent Variable: MMW4
Method: Least Squares
Sample: 1 225
Included observations: 225
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMRP	0.842554	0.067418	12.49753	0.0000
SMB	0.379141	0.068321	5.549374	0.0000
VMG__EW_	-0.028334	0.073897	-0.383425	0.7018
C	-0.003704	0.002536	-1.460714	0.1455

R-squared	0.618371	Mean dependent var	-0.001805
Adjusted R-squared	0.613191	S.D. dependent var	0.051613
S.E. of regression	0.032100	Akaike info criterion	-4.022275
Sum squared resid	0.227727	Schwarz criterion	-3.961544
Log likelihood	456.5059	Hannan-Quinn criter.	-3.997763
F-statistic	119.3655	Durbin-Watson stat	1.578997
Prob(F-statistic)	0.000000		

Dependent Variable: MMW5
Method: Least Squares
Sample: 1 225
Included observations: 225
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMRP	0.889606	0.048229	18.44534	0.0000
SMB	0.364534	0.058451	6.236532	0.0000
VMG__EW_	-0.040960	0.066784	-0.613324	0.5403
C	-0.009112	0.002512	-3.626624	0.0004

R-squared	0.628197	Mean dependent var	-0.007055
Adjusted R-squared	0.623150	S.D. dependent var	0.054585
S.E. of regression	0.033508	Akaike info criterion	-3.936421
Sum squared resid	0.248142	Schwarz criterion	-3.875690
Log likelihood	446.8473	Hannan-Quinn criter.	-3.911910
F-statistic	124.4671	Durbin-Watson stat	1.766881
Prob(F-statistic)	0.000000		

Dependent Variable: MMWWML
Method: Least Squares
Sample: 1 225
Included observations: 225
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMRP	0.399664	0.145526	2.746346	0.0065
SMB	0.412258	0.146290	2.818087	0.0053
VMG__EW_	-0.150288	0.152800	-0.983561	0.3264
C	0.017704	0.005851	3.025743	0.0028

R-squared	0.068319	Mean dependent var	0.017066
Adjusted R-squared	0.055672	S.D. dependent var	0.080299
S.E. of regression	0.078032	Akaike info criterion	-2.245777
Sum squared resid	1.345668	Schwarz criterion	-2.185047
Log likelihood	256.6499	Hannan-Quinn criter.	-2.221266
F-statistic	5.401891	Durbin-Watson stat	1.940216
Prob(F-statistic)	0.001322		

Appendix 1d: Time Series Regression Output – Five (Other) Factor Model Regressions

Dependent Variable: EW1
Method: Least Squares
Sample: 1997M01 2015M08
Included observations: 224
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMRP	0.877330	0.078519	11.17351	0.0000
BETA	0.041349	0.050442	0.819737	0.4133
IDIO	-0.289382	0.074046	-3.908167	0.0001
HLMLL	-0.091437	0.074714	-1.223829	0.2223
RTMRH	0.058183	0.068708	0.846825	0.3980
C	0.008341	0.002830	2.947299	0.0036

R-squared	0.658507	Mean dependent var	0.008584
Adjusted R-squared	0.650675	S.D. dependent var	0.061628
S.E. of regression	0.036425	Akaike info criterion	-3.760722
Sum squared resid	0.289233	Schwarz criterion	-3.669339
Log likelihood	427.2009	Hannan-Quinn criter.	-3.723835
F-statistic	84.07481	Durbin-Watson stat	1.800872
Prob(F-statistic)	0.000000		

Dependent Variable: EW2
Method: Least Squares
Sample: 1997M01 2015M08
Included observations: 224
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMRP	0.701601	0.059587	11.77431	0.0000
BETA	0.052866	0.058493	0.903803	0.3671
HLMLL	-0.099045	0.046680	-2.121773	0.0350
IDIO	-0.111621	0.074810	-1.492066	0.1371
RTMRH	0.183268	0.048118	3.808722	0.0002
C	-4.98E-05	0.002420	-0.020565	0.9836

R-squared	0.621493	Mean dependent var	0.001982
Adjusted R-squared	0.612811	S.D. dependent var	0.048612
S.E. of regression	0.030249	Akaike info criterion	-4.132295
Sum squared resid	0.199469	Schwarz criterion	-4.040912
Log likelihood	468.8171	Hannan-Quinn criter.	-4.095409
F-statistic	71.58928	Durbin-Watson stat	1.687985
Prob(F-statistic)	0.000000		

Dependent Variable: EW3
Method: Least Squares
Sample: 1997M01 2015M08
Included observations: 224
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMRP	0.786060	0.056649	13.87604	0.0000
BETA	0.097304	0.042383	2.295856	0.0226
HLMLL	-0.147859	0.061267	-2.413351	0.0166
IDIO	-0.022612	0.043850	-0.515667	0.6066
RTMRH	0.142682	0.059947	2.380137	0.0182
C	-0.003476	0.002305	-1.507975	0.1330

R-squared	0.653149	Mean dependent var	-0.000160
Adjusted R-squared	0.645193	S.D. dependent var	0.050443
S.E. of regression	0.030047	Akaike info criterion	-4.145697
Sum squared resid	0.196813	Schwarz criterion	-4.054313
Log likelihood	470.3180	Hannan-Quinn criter.	-4.108810
F-statistic	82.10228	Durbin-Watson stat	1.678226
Prob(F-statistic)	0.000000		

Dependent Variable: EW4
Method: Least Squares
Sample: 1997M01 2015M08
Included observations: 224
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMRP	0.671480	0.062560	10.73337	0.0000
BETA	0.039692	0.056069	0.707904	0.4798
HLMLL	0.015661	0.083346	0.187899	0.8511
IDIO	-0.092592	0.051755	-1.789063	0.0750
RTMRH	0.213769	0.073210	2.919937	0.0039
C	-0.004334	0.002607	-1.662708	0.0978

R-squared	0.574066	Mean dependent var	-0.001770
Adjusted R-squared	0.564297	S.D. dependent var	0.051566
S.E. of regression	0.034038	Akaike info criterion	-3.896265
Sum squared resid	0.252570	Schwarz criterion	-3.804881
Log likelihood	442.3816	Hannan-Quinn criter.	-3.859378
F-statistic	58.76339	Durbin-Watson stat	1.542290
Prob(F-statistic)	0.000000		

Dependent Variable: EW5
Method: Least Squares
Sample: 1997M01 2015M08
Included observations: 224

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMRP	0.719748	0.049981	14.40035	0.0000
BETA	-0.018092	0.044213	-0.409208	0.6828
HLMLL	-0.045959	0.060395	-0.760970	0.4475
IDIO	-0.154684	0.054273	-2.850097	0.0048
RTMRH	0.113733	0.052276	2.175630	0.0307
C	-0.007871	0.002468	-3.189305	0.0016

R-squared	0.582898	Mean dependent var	-0.006694
Adjusted R-squared	0.573332	S.D. dependent var	0.054383
S.E. of regression	0.035523	Akaike info criterion	-3.810851
Sum squared resid	0.275091	Schwarz criterion	-3.719468
Log likelihood	432.8153	Hannan-Quinn criter.	-3.773964
F-statistic	60.93090	Durbin-Watson stat	1.736101
Prob(F-statistic)	0.000000		

Dependent Variable: MCW1
Method: Least Squares
Sample: 1997M01 2015M08
Included observations: 224
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMRP	0.897597	0.077195	11.62769	0.0000
BETA	0.038678	0.050364	0.767954	0.4433
HLMLL	-0.068348	0.071890	-0.950735	0.3428
IDIO	-0.271853	0.074723	-3.638150	0.0003
RTMRH	0.044496	0.067696	0.657298	0.5117
C	0.008993	0.002685	3.349604	0.0010

R-squared	0.679169	Mean dependent var	0.009537
Adjusted R-squared	0.671810	S.D. dependent var	0.062221
S.E. of regression	0.035645	Akaike info criterion	-3.803986
Sum squared resid	0.276986	Schwarz criterion	-3.712602
Log likelihood	432.0464	Hannan-Quinn criter.	-3.767099
F-statistic	92.29692	Durbin-Watson stat	1.853367
Prob(F-statistic)	0.000000		

Dependent Variable: MCW2
Method: Least Squares
Sample: 1997M01 2015M08
Included observations: 224
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMRP	0.717358	0.057840	12.40251	0.0000
BETA	0.048047	0.054215	0.886224	0.3765
IDIO	-0.100319	0.069190	-1.449897	0.1485
HLMLL	-0.085152	0.044734	-1.903528	0.0583
RTMRH	0.181772	0.043806	4.149427	0.0000
C	0.000242	0.002239	0.108091	0.9140

R-squared	0.656630	Mean dependent var	0.002482
Adjusted R-squared	0.648754	S.D. dependent var	0.048581
S.E. of regression	0.028792	Akaike info criterion	-4.231013
Sum squared resid	0.180718	Schwarz criterion	-4.139630
Log likelihood	479.8735	Hannan-Quinn criter.	-4.194126
F-statistic	83.37662	Durbin-Watson stat	1.731284
Prob(F-statistic)	0.000000		

Dependent Variable: MCW3
Method: Least Squares
Sample: 1997M01 2015M08
Included observations: 224
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMRP	0.794021	0.054825	14.48283	0.0000
BETA	0.077257	0.041021	1.883364	0.0610
HLMLL	-0.121898	0.060102	-2.028204	0.0438
IDIO	-0.016467	0.041533	-0.396493	0.6921
RTMRH	0.149936	0.058390	2.567860	0.0109
C	-0.002882	0.002184	-1.319546	0.1884

R-squared	0.689136	Mean dependent var	0.000540
Adjusted R-squared	0.682006	S.D. dependent var	0.050415
S.E. of regression	0.028429	Akaike info criterion	-4.256379
Sum squared resid	0.176192	Schwarz criterion	-4.164995
Log likelihood	482.7144	Hannan-Quinn criter.	-4.219492
F-statistic	96.65441	Durbin-Watson stat	1.645605
Prob(F-statistic)	0.000000		

Dependent Variable: MCW4
Method: Least Squares
Sample: 1997M01 2015M08
Included observations: 224

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMRP	0.694827	0.047070	14.76146	0.0000
BETA	0.036835	0.041638	0.884657	0.3773
HLMLL	0.022967	0.056877	0.403803	0.6868
IDIO	-0.082081	0.051112	-1.605895	0.1097
RTMRH	0.219567	0.049231	4.459918	0.0000
C	-0.004029	0.002324	-1.733309	0.0845

R-squared	0.600098	Mean dependent var	-0.001223
Adjusted R-squared	0.590926	S.D. dependent var	0.052306
S.E. of regression	0.033454	Akaike info criterion	-3.930861
Sum squared resid	0.243981	Schwarz criterion	-3.839477
Log likelihood	446.2564	Hannan-Quinn criter.	-3.893974
F-statistic	65.42684	Durbin-Watson stat	1.578043
Prob(F-statistic)	0.000000		

Dependent Variable: MCW5
Method: Least Squares
Sample: 1997M01 2015M08
Included observations: 224
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMRP	0.739775	0.060214	12.28580	0.0000
BETA	-0.023519	0.050128	-0.469170	0.6394
HLMLL	-0.024677	0.076416	-0.322930	0.7471
IDIO	-0.135605	0.055891	-2.426251	0.0161
RTMRH	0.102187	0.072129	1.416727	0.1580
C	-0.007945	0.002705	-2.936760	0.0037

R-squared	0.597411	Mean dependent var	-0.006465
Adjusted R-squared	0.588178	S.D. dependent var	0.055470
S.E. of regression	0.035597	Akaike info criterion	-3.806702
Sum squared resid	0.276235	Schwarz criterion	-3.715318
Log likelihood	432.3506	Hannan-Quinn criter.	-3.769815
F-statistic	64.69914	Durbin-Watson stat	1.729481
Prob(F-statistic)	0.000000		

Dependent Variable: MMW1
Method: Least Squares
Sample: 1997M01 2015M08
Included observations: 224
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMRP	0.887765	0.127558	6.959716	0.0000
BETA	-0.003837	0.078028	-0.049169	0.9608
HLMLL	0.041744	0.163053	0.256013	0.7982
IDIO	-0.534465	0.118907	-4.494799	0.0000
RTMRH	0.060148	0.112973	0.532414	0.5950
C	0.012281	0.005262	2.334060	0.0205

R-squared	0.410411	Mean dependent var	0.010000
Adjusted R-squared	0.396888	S.D. dependent var	0.091705
S.E. of regression	0.071218	Akaike info criterion	-2.419717
Sum squared resid	1.105702	Schwarz criterion	-2.328333
Log likelihood	277.0083	Hannan-Quinn criter.	-2.382830
F-statistic	30.34976	Durbin-Watson stat	1.945649
Prob(F-statistic)	0.000000		

Dependent Variable: MMW2
Method: Least Squares
Sample: 1997M01 2015M08
Included observations: 224
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMRP	0.704002	0.060204	11.69355	0.0000
BETA	0.067416	0.057819	1.165989	0.2449
HLMLL	-0.101481	0.045634	-2.223812	0.0272
IDIO	-0.122341	0.074834	-1.634818	0.1035
RTMRH	0.186385	0.047309	3.939730	0.0001
C	-0.000265	0.002441	-0.108469	0.9137

R-squared	0.617119	Mean dependent var	0.001736
Adjusted R-squared	0.608337	S.D. dependent var	0.048789
S.E. of regression	0.030533	Akaike info criterion	-4.113576
Sum squared resid	0.203238	Schwarz criterion	-4.022193
Log likelihood	466.7206	Hannan-Quinn criter.	-4.076690
F-statistic	70.27345	Durbin-Watson stat	1.708368
Prob(F-statistic)	0.000000		

Dependent Variable: MMW3
Method: Least Squares
Sample: 1997M01 2015M08
Included observations: 224
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMRP	0.779179	0.056595	13.76762	0.0000
BETA	0.093529	0.043063	2.171895	0.0309
HLMLL	-0.144931	0.060140	-2.409876	0.0168
IDIO	-0.015735	0.044195	-0.356042	0.7222
RTMRH	0.144602	0.060055	2.407820	0.0169
C	-0.003614	0.002317	-1.559921	0.1202

R-squared	0.647479	Mean dependent var	-0.000251
Adjusted R-squared	0.639394	S.D. dependent var	0.050292
S.E. of regression	0.030201	Akaike info criterion	-4.135473
Sum squared resid	0.198836	Schwarz criterion	-4.044089
Log likelihood	469.1729	Hannan-Quinn criter.	-4.098586
F-statistic	80.08059	Durbin-Watson stat	1.689421
Prob(F-statistic)	0.000000		

Dependent Variable: MMW4
Method: Least Squares
Sample: 1997M01 2015M08
Included observations: 224
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMRP	0.672992	0.061919	10.86895	0.0000
BETA	0.040111	0.055796	0.718885	0.4730
HLMLL	0.018831	0.083621	0.225200	0.8220
IDIO	-0.097025	0.051506	-1.883771	0.0609
RTMRH	0.213614	0.073530	2.905141	0.0040
C	-0.004349	0.002604	-1.670373	0.0963

R-squared	0.575404	Mean dependent var	-0.001816
Adjusted R-squared	0.565666	S.D. dependent var	0.051729
S.E. of regression	0.034091	Akaike info criterion	-3.893126
Sum squared resid	0.253364	Schwarz criterion	-3.801743
Log likelihood	442.0301	Hannan-Quinn criter.	-3.856239
F-statistic	59.08592	Durbin-Watson stat	1.546417
Prob(F-statistic)	0.000000		

Dependent Variable: MMW5
Method: Least Squares
Sample: 1997M01 2015M08
Included observations: 224
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMRP	0.721929	0.057180	12.62547	0.0000
BETA	-0.022859	0.051618	-0.442846	0.6583
HLMLL	-0.051789	0.069337	-0.746922	0.4559
IDIO	-0.159376	0.053226	-2.994325	0.0031
RTMRH	0.109050	0.072324	1.507788	0.1331
C	-0.008136	0.002716	-2.995263	0.0031

R-squared	0.580693	Mean dependent var	-0.007066
Adjusted R-squared	0.571076	S.D. dependent var	0.054707
S.E. of regression	0.035829	Akaike info criterion	-3.793720
Sum squared resid	0.279844	Schwarz criterion	-3.702336
Log likelihood	430.8966	Hannan-Quinn criter.	-3.756833
F-statistic	60.38108	Durbin-Watson stat	1.734993
Prob(F-statistic)	0.000000		

Dependent Variable: WMLEW
Method: Least Squares
Sample: 1997M01 2015M08
Included observations: 224
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMRP	0.157582	0.096026	1.641043	0.1022
BETA	0.059441	0.059047	1.006680	0.3152
HLMLL	-0.045478	0.121569	-0.374093	0.7087
IDIO	-0.134698	0.096160	-1.400767	0.1627
RTMRH	-0.055549	0.092600	-0.599880	0.5492
C	0.016212	0.003484	4.652855	0.0000

R-squared	0.048337	Mean dependent var	0.015279
Adjusted R-squared	0.026510	S.D. dependent var	0.048126
S.E. of regression	0.047484	Akaike info criterion	-3.230430
Sum squared resid	0.491530	Schwarz criterion	-3.139047
Log likelihood	367.8082	Hannan-Quinn criter.	-3.193543
F-statistic	2.214524	Durbin-Watson stat	1.910364
Prob(F-statistic)	0.053928		

Dependent Variable: WMLMCW
Method: Least Squares
Sample: 1997M01 2015M08
Included observations: 224
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMRP	0.157822	0.101174	1.559900	0.1202
BETA	0.062196	0.060976	1.020013	0.3089
HLMLL	-0.043671	0.129563	-0.337061	0.7364
IDIO	-0.136247	0.103282	-1.319182	0.1885
RTMRH	-0.057691	0.097900	-0.589284	0.5563
C	0.016938	0.003583	4.727111	0.0000

R-squared	0.045749	Mean dependent var	0.016003
Adjusted R-squared	0.023862	S.D. dependent var	0.049877
S.E. of regression	0.049278	Akaike info criterion	-3.156244
Sum squared resid	0.529381	Schwarz criterion	-3.064861
Log likelihood	359.4994	Hannan-Quinn criter.	-3.119358
F-statistic	2.090274	Durbin-Watson stat	1.898745
Prob(F-statistic)	0.067722		

Dependent Variable: WMLMMW
Method: Least Squares
Sample: 1997M01 2015M08
Included observations: 224
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMRP	0.165837	0.155985	1.063159	0.2889
BETA	0.019022	0.083527	0.227737	0.8201
HLMLL	0.093533	0.204818	0.456663	0.6484
IDIO	-0.375090	0.142203	-2.637708	0.0089
RTMRH	-0.048902	0.140941	-0.346965	0.7290
C	0.020417	0.006088	3.353656	0.0009

R-squared	0.074815	Mean dependent var	0.017066
Adjusted R-squared	0.053595	S.D. dependent var	0.080479
S.E. of regression	0.078293	Akaike info criterion	-2.230304
Sum squared resid	1.336285	Schwarz criterion	-2.138921
Log likelihood	255.7940	Hannan-Quinn criter.	-2.193417
F-statistic	3.525719	Durbin-Watson stat	1.885495
Prob(F-statistic)	0.004373		

Appendix 1e: Time Series Regression Output – van Rensburg APT Model Regressions

Dependent Variable: EW1
Method: Least Squares
Sample (adjusted): 1998M03 2015M08
Included observations: 210 after adjustments
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
FINDIETR	0.657882	0.106812	6.159271	0.0000
RESIETR	0.195371	0.067768	2.882946	0.0044
C	0.007013	0.003535	1.983739	0.0486

R-squared	0.575723	Mean dependent var	0.008293
Adjusted R-squared	0.571624	S.D. dependent var	0.062165
S.E. of regression	0.040687	Akaike info criterion	-3.551635
Sum squared resid	0.342674	Schwarz criterion	-3.503820
Log likelihood	375.9217	Hannan-Quinn criter.	-3.532305
F-statistic	140.4446	Durbin-Watson stat	1.571839
Prob(F-statistic)	0.000000		

Dependent Variable: EW2
Method: Least Squares
Sample (adjusted): 1998M03 2015M08
Included observations: 210 after adjustments
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
FINDIETR	0.671003	0.053770	12.47917	0.0000
RESIETR	0.024882	0.036194	0.687460	0.4926
C	0.001608	0.002471	0.650877	0.5158

R-squared	0.637275	Mean dependent var	0.002103
Adjusted R-squared	0.633771	S.D. dependent var	0.048559
S.E. of regression	0.029386	Akaike info criterion	-4.202405
Sum squared resid	0.178754	Schwarz criterion	-4.154589
Log likelihood	444.2525	Hannan-Quinn criter.	-4.183075
F-statistic	181.8404	Durbin-Watson stat	1.664620
Prob(F-statistic)	0.000000		

Dependent Variable: EW3
Method: Least Squares
Sample (adjusted): 1998M03 2015M08
Included observations: 210 after adjustments
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
FINDIETR	0.666747	0.054946	12.13449	0.0000
RESIETR	0.072994	0.034858	2.094031	0.0375
C	-0.000431	0.002366	-0.182336	0.8555

R-squared	0.654853	Mean dependent var	0.000284
Adjusted R-squared	0.651518	S.D. dependent var	0.050446
S.E. of regression	0.029780	Akaike info criterion	-4.175803
Sum squared resid	0.183573	Schwarz criterion	-4.127987
Log likelihood	441.4593	Hannan-Quinn criter.	-4.156473
F-statistic	196.3722	Durbin-Watson stat	1.700852
Prob(F-statistic)	0.000000		

Dependent Variable: EW4
Method: Least Squares
Sample (adjusted): 1998M03 2015M08
Included observations: 210 after adjustments
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
FINDIETR	0.766631	0.052417	14.62557	0.0000
RESIETR	-0.014658	0.035490	-0.413011	0.6800
C	-0.000497	0.002405	-0.206522	0.8366

R-squared	0.667775	Mean dependent var	-0.000132
Adjusted R-squared	0.664565	S.D. dependent var	0.051952
S.E. of regression	0.030089	Akaike info criterion	-4.155148
Sum squared resid	0.187404	Schwarz criterion	-4.107333
Log likelihood	439.2906	Hannan-Quinn criter.	-4.135818
F-statistic	208.0354	Durbin-Watson stat	1.557977
Prob(F-statistic)	0.000000		

Dependent Variable: EW5
Method: Least Squares
Sample (adjusted): 1998M03 2015M08
Included observations: 210 after adjustments
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
FINDIETR	0.636379	0.052177	12.19654	0.0000
RESIETR	0.135521	0.041615	3.256579	0.0013
C	-0.006558	0.002781	-2.357627	0.0193

R-squared	0.591990	Mean dependent var	-0.005568
Adjusted R-squared	0.588048	S.D. dependent var	0.055227
S.E. of regression	0.035447	Akaike info criterion	-3.827379
Sum squared resid	0.260092	Schwarz criterion	-3.779563
Log likelihood	404.8748	Hannan-Quinn criter.	-3.808049
F-statistic	150.1703	Durbin-Watson stat	1.766090
Prob(F-statistic)	0.000000		

Dependent Variable: EWWML
Method: Least Squares
Sample (adjusted): 1998M03 2015M08
Included observations: 210 after adjustments
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
FINDIETR	0.021504	0.122097	0.176119	0.8604
RESIETR	0.059850	0.080120	0.747012	0.4559
C	0.013570	0.003809	3.562613	0.0005

R-squared	0.013587	Mean dependent var	0.013861
Adjusted R-squared	0.004057	S.D. dependent var	0.048164
S.E. of regression	0.048066	Akaike info criterion	-3.218301
Sum squared resid	0.478240	Schwarz criterion	-3.170486
Log likelihood	340.9217	Hannan-Quinn criter.	-3.198971
F-statistic	1.425638	Durbin-Watson stat	1.833825
Prob(F-statistic)	0.242705		

Dependent Variable: MCW1
Method: Least Squares
Sample (adjusted): 1998M03 2015M08
Included observations: 210 after adjustments
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
FINDIETR	0.657774	0.105947	6.208495	0.0000
RESIETR	0.219305	0.068256	3.212986	0.0015
C	0.007856	0.003425	2.294128	0.0228

R-squared	0.598410	Mean dependent var	0.009247
Adjusted R-squared	0.594529	S.D. dependent var	0.062863
S.E. of regression	0.040029	Akaike info criterion	-3.584233
Sum squared resid	0.331684	Schwarz criterion	-3.536417
Log likelihood	379.3444	Hannan-Quinn criter.	-3.564903
F-statistic	154.2252	Durbin-Watson stat	1.598894
Prob(F-statistic)	0.000000		

Dependent Variable: MCW2
Method: Least Squares
Sample (adjusted): 1998M03 2015M08
Included observations: 210 after adjustments
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
FINDIETR	0.682020	0.051582	13.22198	0.0000
RESIETR	0.034899	0.033798	1.032590	0.3030
C	0.002086	0.002301	0.906549	0.3657

R-squared	0.675898	Mean dependent var	0.002633
Adjusted R-squared	0.672767	S.D. dependent var	0.048457
S.E. of regression	0.027720	Akaike info criterion	-4.319175
Sum squared resid	0.159053	Schwarz criterion	-4.271359
Log likelihood	456.5133	Hannan-Quinn criter.	-4.299845
F-statistic	215.8440	Durbin-Watson stat	1.690571
Prob(F-statistic)	0.000000		

Dependent Variable: MCW3
Method: Least Squares
Sample (adjusted): 1998M03 2015M08
Included observations: 210 after adjustments
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
FINDIETR	0.684687	0.051077	13.40489	0.0000
RESIETR	0.080570	0.033636	2.395350	0.0175
C	0.000255	0.002197	0.115851	0.9079

R-squared	0.701477	Mean dependent var	0.001016
Adjusted R-squared	0.698592	S.D. dependent var	0.050392
S.E. of regression	0.027665	Akaike info criterion	-4.323089
Sum squared resid	0.158432	Schwarz criterion	-4.275273
Log likelihood	456.9244	Hannan-Quinn criter.	-4.303759
F-statistic	243.2064	Durbin-Watson stat	1.680588
Prob(F-statistic)	0.000000		

Dependent Variable: MCW4
Method: Least Squares
Sample (adjusted): 1998M03 2015M08
Included observations: 210 after adjustments
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
FINDIETR	0.781427	0.048652	16.06147	0.0000
RESIETR	-0.003118	0.035089	-0.088850	0.9293
C	4.36E-05	0.002309	0.018859	0.9850

R-squared	0.689642	Mean dependent var	0.000470
Adjusted R-squared	0.686644	S.D. dependent var	0.052689
S.E. of regression	0.029494	Akaike info criterion	-4.195060
Sum squared resid	0.180072	Schwarz criterion	-4.147244
Log likelihood	443.4813	Hannan-Quinn criter.	-4.175729
F-statistic	229.9864	Durbin-Watson stat	1.611610
Prob(F-statistic)	0.000000		

Dependent Variable: MCW5
Method: Least Squares
Sample (adjusted): 1998M03 2015M08
Included observations: 210 after adjustments
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
FINDIETR	0.644638	0.052312	12.32301	0.0000
RESIETR	0.154338	0.044654	3.456285	0.0007
C	-0.006439	0.002773	-2.321746	0.0212

R-squared	0.610850	Mean dependent var	-0.005358
Adjusted R-squared	0.607090	S.D. dependent var	0.056323
S.E. of regression	0.035305	Akaike info criterion	-3.835417
Sum squared resid	0.258010	Schwarz criterion	-3.787601
Log likelihood	405.7187	Hannan-Quinn criter.	-3.816086
F-statistic	162.4644	Durbin-Watson stat	1.771316
Prob(F-statistic)	0.000000		

Dependent Variable: MCWML
Method: Least Squares
Sample (adjusted): 1998M03 2015M08
Included observations: 210 after adjustments
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
FINDIETR	0.013136	0.123833	0.106077	0.9156
RESIETR	0.064967	0.088899	0.730802	0.4657
C	0.014296	0.003964	3.606627	0.0004

R-squared	0.013140	Mean dependent var	0.014605
Adjusted R-squared	0.003605	S.D. dependent var	0.049999
S.E. of regression	0.049909	Akaike info criterion	-3.143057
Sum squared resid	0.515614	Schwarz criterion	-3.095241
Log likelihood	333.0210	Hannan-Quinn criter.	-3.123727
F-statistic	1.378110	Durbin-Watson stat	1.820506
Prob(F-statistic)	0.254357		

Dependent Variable: MMW1
Method: Least Squares
Sample (adjusted): 1998M03 2015M08
Included observations: 210 after adjustments
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
FINDIETR	0.599667	0.136503	4.393062	0.0000
RESIETR	0.285159	0.101132	2.819662	0.0053
C	0.007948	0.005842	1.360566	0.1751

R-squared	0.295726	Mean dependent var	0.009613
Adjusted R-squared	0.288921	S.D. dependent var	0.091626
S.E. of regression	0.077264	Akaike info criterion	-2.268989
Sum squared resid	1.235739	Schwarz criterion	-2.221174
Log likelihood	241.2439	Hannan-Quinn criter.	-2.249659
F-statistic	43.45986	Durbin-Watson stat	1.856392
Prob(F-statistic)	0.000000		

Dependent Variable: MMW2
Method: Least Squares
Sample (adjusted): 1998M03 2015M08
Included observations: 210 after adjustments
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
FINDIETR	0.666344	0.056192	11.85835	0.0000
RESIETR	0.026722	0.035994	0.742412	0.4587
C	0.001318	0.002510	0.525169	0.6000

R-squared	0.626022	Mean dependent var	0.001819
Adjusted R-squared	0.622409	S.D. dependent var	0.048768
S.E. of regression	0.029967	Akaike info criterion	-4.163258
Sum squared resid	0.185890	Schwarz criterion	-4.115443
Log likelihood	440.1421	Hannan-Quinn criter.	-4.143928
F-statistic	173.2541	Durbin-Watson stat	1.664406
Prob(F-statistic)	0.000000		

Dependent Variable: MMW3
Method: Least Squares
Sample (adjusted): 1998M03 2015M08
Included observations: 210 after adjustments
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
FINDIETR	0.666965	0.054225	12.29986	0.0000
RESIETR	0.068716	0.034843	1.972149	0.0499
C	-0.000504	0.002346	-0.214847	0.8301

R-squared	0.652556	Mean dependent var	0.000192
Adjusted R-squared	0.649199	S.D. dependent var	0.050284
S.E. of regression	0.029783	Akaike info criterion	-4.175595
Sum squared resid	0.183611	Schwarz criterion	-4.127779
Log likelihood	441.4375	Hannan-Quinn criter.	-4.156265
F-statistic	194.3900	Durbin-Watson stat	1.727108
Prob(F-statistic)	0.000000		

Dependent Variable: MMW4
Method: Least Squares
Sample (adjusted): 1998M03 2015M08
Included observations: 210 after adjustments
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
FINDIETR	0.768040	0.052385	14.66141	0.0000
RESIETR	-0.012853	0.035813	-0.358874	0.7201
C	-0.000543	0.002394	-0.226799	0.8208

R-squared	0.668644	Mean dependent var	-0.000170
Adjusted R-squared	0.665442	S.D. dependent var	0.052103
S.E. of regression	0.030137	Akaike info criterion	-4.151937
Sum squared resid	0.188007	Schwarz criterion	-4.104121
Log likelihood	438.9534	Hannan-Quinn criter.	-4.132607
F-statistic	208.8528	Durbin-Watson stat	1.557831
Prob(F-statistic)	0.000000		

Dependent Variable: MMW5
Method: Least Squares
Sample (adjusted): 1998M03 2015M08
Included observations: 210 after adjustments
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
FINDIETR	0.630723	0.053598	11.76756	0.0000
RESIETR	0.142522	0.042425	3.359383	0.0009
C	-0.006978	0.002823	-2.471593	0.0143

R-squared	0.587029	Mean dependent var	-0.005959
Adjusted R-squared	0.583039	S.D. dependent var	0.055577
S.E. of regression	0.035887	Akaike info criterion	-3.802680
Sum squared resid	0.266596	Schwarz criterion	-3.754865
Log likelihood	402.2814	Hannan-Quinn criter.	-3.783350
F-statistic	147.1227	Durbin-Watson stat	1.760126
Prob(F-statistic)	0.000000		

Dependent Variable: MMWWML
Method: Least Squares
Sample (adjusted): 1998M03 2015M08
Included observations: 210 after adjustments
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
FINDIETR	-0.031055	0.151735	-0.204668	0.8380
RESIETR	0.142637	0.111035	1.284611	0.2004
C	0.014926	0.006251	2.387837	0.0178

R-squared	0.018384	Mean dependent var	0.015572
Adjusted R-squared	0.008900	S.D. dependent var	0.080326
S.E. of regression	0.079968	Akaike info criterion	-2.200200
Sum squared resid	1.323738	Schwarz criterion	-2.152384
Log likelihood	234.0210	Hannan-Quinn criter.	-2.180869
F-statistic	1.938413	Durbin-Watson stat	1.899910
Prob(F-statistic)	0.146536		

Appendix 1f: Time-Series Regression Output – Stepwise Regression (Equally Weighted)

Portfolio	α	β_{J203}	β_{FINDI}	β_{RESI}	$\beta_{Low\ Beta}$	$\beta_{Low\ Vol}$	β_{Size}	β_{Value}	$\beta_{Liquidity}$	β_{USDZAR}	Adj. R^2
Winner	0.0058	0.9193	0.1712			-0.1294	0.4836				74.58%
	0.0000* **	**0.0000*** **	**0.0350*** **			**0.0111** **	**0.0000*** **				
2	0.0028	1.2095		-0.3234			0.3049			0.0649	76.97%
	0.1003 **	**0.0000*** **		**0.0000*** **			**0.0000*** **			**0.0755** *	
3	-0.0015	1.2721		-0.3142		0.1218	0.2890	0.1175	-0.1197		76.32%
	0.4138	**0.0000*** **		**0.0000*** **		**0.0026*** **	**0.0000*** **	**0.0089*** **	**0.0070** **		
4	-0.0058	0.6554	0.4530	-0.1937			0.2957	0.0936			74.22%
	0.0314 **	**0.0024*** **	**0.0010*** **	**0.0268** **			**0.0000*** **	**0.0509** *			
Loser	-0.0119	0.5520	0.3520		-0.0830		0.3567				65.72%
	0.0000* **	**0.0000*** **	**0.0000*** **		**0.0350** **		**0.0000*** **				
WML	0.0288	1.7928	-1.0766	-0.5977							10.85%
	0.0000* **	**0.0000*** **	**0.0000*** **	**0.0000*** **							

Appendix 1g: Time Series Regression Output – Stepwise Regression (Momentum Rank Weighted)

Portfolio	α	β_{J203}	β_{FINDI}	β_{RESI}	$\beta_{Low\ Beta}$	$\beta_{Low\ Vol}$	β_{Size}	β_{Value}	$\beta_{Liquidity}$	β_{USDZAR}	Adj. R^2
Winner	0.0186	2.1679	-0.5910	-0.3940		-0.2760	0.5802				46.09%
	0.0069* **	**0.0001*** **	**0.0927***	**0.0641***		**0.0141** **	**0.0000*** **				
2	0.0024	1.1999		-0.3162			0.3073		-0.0855	0.0706	75.72%
	0.1641	**0.0000*** **		**0.0000*** **			**0.0000*** **		**0.0467** **	**0.0613***	
3	-0.0015	1.2658		-0.3133		0.1289	0.2934	0.1096	-0.1175		75.92%
	0.3870	**0.0000*** **		**0.0000*** **		**0.0016*** **	**0.0000*** **	**0.0150** **	**0.0084** **		
4	-0.0101	0.2843	0.6297				0.3481				71.85%
	0.0000* **	**0.0001*** **	**0.0000*** **				**0.0000*** **				
Loser	-0.0166		0.6993	0.2181	-0.0827		0.3810				65.71%
	0.0000* **		**0.0000*** **	**0.0000*** **	**0.0439** **		**0.0000*** **				
WML	0.0324	2.1802	-1.2998	-0.5748			0.3296				9.37%
	0.0000* **	**0.0004*** **	**0.0010*** **	**0.0173** **			**0.0141** **				

Appendix 2a: Redundant Fixed Effects

Redundant Fixed Effects Tests			
Effects Test	Statistic	d.f.	Prob.
Cross-section F	1.941974	(212,4008)	0.0000
Cross-section Chi-square	416.930090	212	0.0000
Period F	36.388580	(36,4008)	0.0000
Period Chi-square	1205.871296	36	0.0000
Cross-Section/Period F	7.146856	(248,4008)	0.0000
Cross-Section/Period Chi-square	1561.408741	248	0.0000

Appendix 2b: Hausman Tests (Random Effects)

Correlated Random Effects - Hausman Test Test cross-section random effects			
Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random	271.055924	7	0.0000
** WARNING: estimated cross-section random effects variance is zero.			

Correlated Random Effects - Hausman Test Test period random effects			
Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Period random	13.699083	7	0.0568