INVESTIGATING THE CONDITIONAL CORRELATIONS OF STYLE PORTFOLIOS ON THE JSE

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ABSTRACT

Negative market shocks can drive the standard deviation of the broader market several iterations away from its mean. During these periods, international research, mainly originating from the stock markets of the United States, has documented an increase in correlation between actively managed portfolios and the broader market index. This research found that the conditional correlation between the actively managed portfolio and the market increased more on the left-tail than the right-tail as standard deviations increased on either side. The correlations are conditional in the sense that the sample points used to calculate the correlation are only measured from the daily trading days when the portfolio and the market exhibit the same standard deviation move in the same direction. The correlation profile then measures the conditional correlation between the portfolio and the market across the standard deviation spectrum. It is a noteworthy cause to investigate portfolio conditional correlation as this will help document the reaction of the portfolio to the market for varying degrees of standard deviation moves. The reactions of each style portfolio to the market will be compared against each other. By reviewing correlation of the various style portfolios at the same standard deviation levels will help determine which portfolios are more robust under the advances and declines of the market. It is useful for portfolio design to consider whether the portfolio has a diminishing ability to withstand a market shock in times of an extreme market move caused by heightened volatility. An undesirable portfolio will have a left tail that has an increasing positive relationship between correlation and standard deviation – the bigger the market shock the more the portfolio begins to resemble the market. Equally concerning is a portfolio with a right-tail with declining correlation as standard deviation is increased - for market advances the portfolio does not closely track the market, with below satisfactory correlation. The benefit of this knowledge will have a far reaching impact on portfolio design. This study adopts style portfolios derived from stocks listed on the JSE as a proxy for actively managed portfolios. Shares are sorted into style portfolios according to size, price-to-earnings ratio, dividend yield and volume traded. Each style factor metric is ranked in ascending order and a median split allows for the formation of sub-portfolios. To measure correlation symmetry in a tangible manner, piecewise linear regression and GARCH-M models are both considered. GARCH models can be sensitive to reduced data sets and when possible need to be fitted to a sample which incorporates an expansive data set. Hence the GARCH-M was fitted to the left and right-tails, as two complete samples, whereby the piecewise linear regression was used on the samples derived at the individual exceedance levels. The models were compared and both conclude evidence of correlation asymmetry amongst sub-portfolios. The findings concur with other international studies on conditional correlations. Over the 10-year study period, the positive tail of the high-volume sub-portfolio has the highest average correlation and tracks the market the closest for advances. For the negative tail the lowest average correlation on the downside is for the low-PE portfolio and tracks the market the least for declines.

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CHAPTER ONE

INTRODUCTION

1.1 BACKGROUND

A salient feature of any investment portfolio is to preserve capital as best as possible amidst declines in the broader equity market. This characteristic is a precept to prudent asset management. Equally as important as capital preservation is capital growth. Without capital growth in excess of inflation the portfolio’s value will decline in real terms over time hence when the broader market advances the portfolio should enjoy the same. These ying and yang features of a portfolio should not be viewed independently. The degree of symmetry of the left and right tails when compared should be considered in conjunction when constructing a portfolio. Beginning with King and Wadhwani (1990), evidence began to accumulate that international correlation tended to increase during a stock market crisis. Moreover, the crash of 1987 suggests evidence that an increase in volatility leads in turn to an increase in the size of contagion effects, whereby volatility, in part, can be self-sustaining.

Later Kritzman, Lowry, and Van Royen (2002), using conditional correlations, developed evidence that asset class correlations, mainly focused on the U.S., decrease during periods of market turbulence. Later extending this idea on the U.S. stock market, Gulko (2002) found that stocks and bonds decouple during market crashes. Regardless of these findings favouring diversification, studies have emerged documenting evidence of correlation asymmetries, showing less diversification in down markets than in up markets. According to Page and Taborsky (2010) from January 1970 to February 2008, when both the U.S. and World ex-U.S. stock markets were up more than one standard deviation above their full-sample mean, the correlation between them was -17%. In contrast, when both markets were down more than one standard deviation, the correlation between them was +76%. The authors have uncovered a clear pattern of asymmetry and this assertion is the backbone of this study.

1.2 PROBLEM STATEMENT

During periods of severe stress in the financial markets equities become increasingly correlated and one of the quintessential purposes of active portfolio design, primarily portfolio protection in a down market, often dissolves. International studies conducted by Ang and Chen (2002) and Chua, Kritzman and Page (2009) have shown that large sigma moves away from the mean result in equities becoming increasingly correlated with the broader market. These periods of turbulence result in equity portfolios becoming highly correlated with the overall market. A major destroyer of an investor's wealth is a portfolio that mimics the market during a market correction or stock market crash. This results in the portfolio being indistinguishable from the market index. In an ideal world a typical investor will seek out an investment portfolio that will rally with the broader gains of the overall stock market and will decouple in a sell-off. Ideally the constructed portfolio will need to be impartial to market moves on the downside and track the market as much as possible on the upside.

South African studies have yielded empirical evidence in favour of style factors as a strong predictor of returns. For example Fraser and Page (2000) validated momentum and value strategies as good predictors of returns on the Johannesburg Stock Exchange (JSE) Industrial sector. Incorporating these two style factors into their study, Van Rensburg and Robertson (2003a) broadly determined the identity of style based factors that would explain the cross-section of JSE returns. In the same year as their first study, Van Rensburg and Robertson (2003b) selected the size and price-to-earnings (PE) variables for a more detailed examination and conclude that beta is inversely related to returns as small firms and low PE stocks earn higher average returns and have lower betas. Using this knowledge as a precept to approaching portfolio design in terms of symmetric or asymmetric tendencies (either side of the mean) it will be useful to clarify which style designed portfolios are able to provide benefits to the JSE investor. These researchers provide evidence that style factors are present in the South African stock market. However it is not clear whether style attributes are also able to provide diversification benefits for the JSE. More precisely to what extent share portfolios built around style attributes offer insulation in a down market whilst at the same time hitching onto market upswings and participating in the gains of the broader market index. Investors need to be concerned with the tails of their portfolios as major moves in the market index, on the upside and downside, are often driven by exogenous factors which we are unable to forecast and have the nature to influence investor sentiment. These 'blind spots' are hard to predict and can range from a sudden and spectacular failure of some large state-owned Chinese bank to a record breaking oil find in the middle of the Karroo! Stock markets react to these news events and stock prices can react in an ungraceful manner. Portfolios need to be constructed in such a manner that they are prepared against unexpected shocks and hence for portfolio design purposes it is worth investigating the tails of style based portfolios during large sigma moves away from the mean.

1.3 RESEARCH OBJECTIVES

The study will investigate style portfolios on the JSE from 2003-2012 and begin by uncovering whether the correlation between the individual style sub-portfolio in question and the market index is symmetric or asymmetric. Once this degree of symmetry is known, the next step is to determine whether the symmetry or asymmetry of the correlation profile presents a benefit or harm to the portfolio investor. A portfolio with a favourable correlation profile will track the market closely for advances in the market (right tail) and will be impartial to market declines (left tail). At a sub-portfolio level the correlation profiles can be compared for both the right and left tails and it can be determined which portfolio has the better correlation profile. This can arm the investor with the behavioural knowledge of style sub-portfolios and their reaction to the market under the two different tail extremities. This knowledge can be used to design a portfolio according to an individual's unique utility needs - based on previous evidence that a portfolio's correlation profile will behave in a predictable manner to the market's move.

The conditional correlations taken from the style portfolio and the market distributions will need to be examined in conjunction including both the upside (positive tails) and downside (negative tails). The correlation data will be measured at periods when both the market and the respective portfolio register moves in their daily returns that result in the individual standard deviations matching in both sign and magnitude. Only moves on the same trading day will be included. The objective is to determine within each style portfolio which sub-portfolio created has a superior correlation profile.
Precisely the research analyses the positive and negative tails separately via a one sided test and seeks to determine whether:

- large cap stock portfolios have a more favourable correlation profile than the small cap stock portfolios for conditional correlations along the right tail.
- large cap stock portfolios have a more favourable correlation profile than the small cap stock portfolios for conditional correlations along the left tail.

- value stock portfolios have a more favourable correlation profile than the growth stock portfolios for conditional correlations along the right tail.
- value stock portfolios have a more favourable correlation profile than the growth stock portfolios for conditional correlations along the left tail.
- more actively traded stock portfolios (high volume) have a more favourable correlation profile than the lesser traded stock portfolios (low volume) for conditional correlations along the right tail.
- more actively traded stock portfolios (high volume) have a more favourable correlation profile than the lesser traded stock portfolios (low volume) for the left tail.
- high dividend yield stock portfolios have a more favourable correlation profile than the low dividend yield stock portfolios for conditional correlations along the right tail.
- high dividend yield stock portfolios have a more favourable correlation profile than the low dividend yield stock portfolios for conditional correlations along the left tail.

1.4 RESEARCH HYPOTHESES

The null hypotheses is repeated individually for each exceedance level point which is comprised of the standard deviation set of 0.0σ, 0.5σ, 1.0σ and 1.5σ for the positive tail and -1.5σ, -1.0σ, -0.5σ and 0.0σ for the negative tail. The point 0.0σ is taken into consideration twice when measuring either side of the mean but is not double counted in the results as data entering the positive tail data set is governed by the operator ≥ (greater than and equal to) and data included in the negative tail data set is governed by the operator < (less than). For illustration purposes only the +1σ and -1σ points are shown in the explicit hypotheses below, but for the empirical tests the entire standard deviation set is tested.

As mentioned in section 3.3 of the methodology the sub-portfolios are created according to a median split. Under each style factor two sub-portfolios are created. Using the size factor as an example, the two sub-portfolios created will be the large and small cap portfolios. A sub-portfolio is considered superior to its sub-portfolio counterpart by measuring the difference in the two respective sub-portfolio correlations at a specific standard deviation point and interpreting the result. For illustration purposes to explain the interpretation of the result, we will stay with the sub-portfolios of large and small cap portfolios and focus on the point standard deviation +1 (located on the right tail). The null hypothesis would be that the correlation at +1σ for the large cap portfolio is equal to the correlation at +1σ for the small cap portfolio (remembering that the correlation of both sub-portfolios are individually conditional on the market also having moved +1σ away from its own mean). We use the strict inequality "greater than" for the alternate hypothesis and hence select a one sided test. If "not equal to" was also used in the alternate hypothesis it would be a two sided test. The alternate hypothesis will be that the large portfolio correlation is greater than the small portfolio correlation at standard deviation point +1σ. The null hypotheses will therefore be rejected if the large cap portfolio has a greater correlation than the small cap portfolio. When considering the positive tail a rejection of the null hypothesis will result in the conclusion that the large cap portfolio has a more favourable correlation to the portfolio investor at +1σ as it will be more correlated (track the market closer) when the market advances +1σ away from its own mean. The tests will be conducted at a 5% level of significance.

Inversely the opposite applies when examining the negative tail (left tail). For the left tail the strict inequality "less than" is used for the alternate hypothesis and again a one sided test selected. If we examine the same sub-portfolios but this time at the -1σ level, an investor would consider the large cap portfolio to have a favourable correlation profile to the small portfolio if the large cap portfolio has a correlation with the market that is lower than the small cap portfolio (the large cap portfolio tracks the market less than the small cap portfolio for a -1σ decline in the market). The null hypothesis for the negative tail would look slightly different to the null hypothesis when the positive tail was examined. The null hypothesis would be restated as the correlation at -1σ for the large cap portfolio is equal to the correlation at -1σ for the small cap portfolio (again remembering that the correlation of both sub-portfolios are independently conditional on the market also having moved -1σ away from its own mean). If the large cap portfolio has a smaller correlation than the small cap portfolio the null hypotheses will be rejected. A rejection of the null hypothesis will result in the conclusion that the large cap portfolio has a more favourable correlation for the portfolio investor due to the reason that at -1σ it will be less correlated with the market when the market declines -1σ away from its mean (the large cap portfolio tracks the market less than the small cap portfolio for a -1σ decline). Again keeping in mind that the results of the null hypothesis need to be statistically significant at the 5% level to be statistically relevant.

The explicit null hypotheses are as follows:

Hypotheses for large and small firm portfolios:

$H0_1$: The conditional correlation at +1σ for the Large firm portfolio and the market is equal to the conditional correlation at +1σ for the Small firm portfolio and the market. (Repeated for each point of the set 0.0σ, 0.5σ, 1.0σ, 1.5σ)
$H0_2$: The conditional correlation at -1σ for the Large firm portfolio and the market is equal to the conditional correlation at -1σ for the Small firm portfolio and the market. (Repeated for each point of the set -1.5σ, -1.0σ, -0.5σ, 0.0σ)

Hypotheses for low and high price-to-earnings portfolios:
$H0_3$: The conditional correlation at +1σ for the low price-to-earnings portfolio and the market is equal to the conditional correlation at +1σ for the high price-to-earnings portfolio and the market. (Repeated for each point of the set 0.0σ, 0.5σ, 1.0σ, 1.5σ)
$H0_4$: The conditional correlation at -1σ for the low price-to-earnings portfolio and the market is equal to the conditional correlation at -1σ for the high price-to-earnings portfolio and the market. (Repeated for each point of the set -1.5σ, -1.0σ, -0.5σ, 0.0σ)

Hypotheses for a portfolio comprised of more actively traded stocks and a portfolio comprised of lesser traded stocks:
$H0_5$: The conditional correlation at +1σ for a more actively traded portfolio and the market is equal to the conditional correlation at +1σ for a lesser traded portfolio and the market. (Repeated for each point of the set 0.0σ, 0.5σ, 1.0σ, 1.5σ)
$H0_6$: The conditional correlation at -1σ for a more actively traded portfolio and the market is equal to the conditional correlation at -1σ for a lesser traded portfolio and the market. (Repeated for each point of the set -1.5σ, -1.0σ, -0.5σ, 0.0σ)

Hypotheses for high and low dividend portfolios:
$H0_7$: The conditional correlation at +1σ for a high dividend portfolio and the market is equal to the conditional correlation at +1σ for a low dividend portfolio and the market. (Repeated for each point of the set 0.0σ, 0.5σ, 1.0σ, 1.5σ)
$H0_8$: The conditional correlation at -1σ for a high dividend portfolio and the market is equal to the conditional correlation at -1σ for a low dividend portfolio and the market. (Repeated for each point of the set -1.5σ, -1.0σ, -0.5σ, 0.0σ)

1.5 CONTRIBUTIONS

This study puts a new angle on style factors from a South African context. It acknowledges previous seminal research of JSE style anomalies such as Van Rensburg (2001), Van Rensburg and Robertson (2003a and 2003b), Auret and Sinclaire (2006) and Hoffman (2012) and combines this outlook with conditional correlation. The main distinguishing factor is that the research takes a new step by overlaying a conditional correlation framework on portfolios designed according to style. This conditional correlation overlay allows the behaviour of style-based portfolios to be observed in conjunction with the market during a broad range of market conditions.

This method of measurement provides a new tool to evaluate the performance of a portfolio. Correlation profiles running from the left to the right tail are formed, been made up of the correlations at each standard deviation increment. After a full correlation profile of each style portfolio with the market is formed, it then allows the correlation profiles between sub-portfolios to be compared individually across the left and right tails. This allows unfavourable correlation profiles to be flagged and potential pitfalls can be avoided. These pitfalls can manifest themselves in a sub-portfolio that lags behind in rallies (low correlation with the market and minimal tracking ability) and during a selloff becomes indistinguishable from the market by tracking it downwards (high correlation with the market with tight tracking). From a broader South African view there is potential for this perspective on portfolio evaluation to add to the local field of portfolio design and architecture as it will document portfolio tail behaviour at the extremities. This paper will also be adding to the limited but valuable research pool of conditional correlations in emerging markets.

1.6 DELIMITATIONS

- The research study does not provide a forecast of future returns. The knowledge gained from correlation symmetry is not sufficient to use these findings to “beat the market”. Previous researchers have attempted to harness an active trading strategy onto the knowledge of symmetry to try predict future returns by using conditional correlations to group portfolios into periods of high and low volatility regimes (exceedance bands), for example, Gulko (2002) recommended a regime switching model based on mean-variance. To its detriment, the research relied on too many rigid assumptions which nullified the predictive power of the model. The strategy called for some rigid assumptions such as the need to switch to an all bond portfolio following a one-day crash. This strategy is based on the assumption that one month after a crash bonds will always outperform stocks. A “black box” approach of this nature relies on too many broad assumptions that all need to simultaneously hold up for a dynamic strategy to be successful. Portfolio management should be like the design of aeroplanes: withstand all conditions including the occasional bit of turbulence. The goal is not to build a predictive model, attempting to foresee future shifts in overall volatility, but to rather flag portfolios that best perform in a single specific period of volatility. However, the same portfolio will not be insulated across all volatility regimes. Future research can explore down the path of optimizing the best combination of sub-portfolios to build the best portfolio of portfolios.

- Empirical correlations are not compared to the correlations from a simulated normal distribution. In a conditional correlation study on the US market by Chua, Kritzman and Page (2009) it was noted that correlation bias may be introduced by focusing on sub-samples. The sub-samples are the daily returns included at each exceedance level. By excluding the daily returns falling outside each standard deviation group, for example, if the data is conditioned to demonstrate any possible difference between the +1 standard deviation pairs versus the -1 standard deviation pairs, all standard deviation pairs in between are ignored, the researchers acknowledge that this removal of the “in-between” data, which is irrelevant to the focal point, may unbalance the distribution curve which could have represented a normal distribution in its unaltered form. The authors proceeded to simulate a normal distribution with the conditioned daily returns and the conclusion is that there is no significant difference between the empirical correlation findings and the correlation implied by simulating a normal distribution. As this study acknowledges the return data is already non-normal in its unconditional form (before conditioning into sub-samples), it is concluded that it is highly unlikely that any findings will be spurious in nature due to conditioning of the standard deviation pair. However minor this may seem, it is included as a delimitation.

1.7 SUMMARY OF MAIN FINDINGS

The key findings of this dissertation are considered to be:

- Correlation asymmetry is present across all four style portfolios investigated. The positive tail of the correlation curve does not mirror the negative tail. This indicates that style portfolios react differently to upside than downside moves of the market.

- Style portfolios are more correlated with the market for downside moves than upside moves. The correlations between the style and market portfolios are comparatively higher for negative standard deviation moves than equal positive standard deviation moves. It is concluded that style portfolios become increasingly more correlated with the broader market, the greater the decline in the market.
- The correlation profiles of portfolios consisting of stocks with larger market caps (Large firm) are more favourable on the right tail than portfolios comprised of smaller market cap stocks (Small firm). For the left tail the Small firm portfolio has a more favourable correlation profile.
- Similarly, portfolios ranked and sorted according to PE ratios reflect a more favourable correlation profile on the right tail for higher PE stocks (High-PE) than lower PE stocks (Low-PE). The opposite occurs for the left tail with the Low-PE portfolio having a more favourable correlation profile.
- Portfolios made up of higher dividend yield stocks (High-DY) have a more favourable correlation profile than lower dividend yield stocks (Low-DY). During downside moves, the High-DY portfolio behaves in a similar fashion on both sides of the mean. Conversely the Low-DY portfolio has more of a asymmetric correlation profile with differing behaviour either side of the tails as standard deviation is increased. Again the left tail results are inverse to the right tail results with the more favourable correlation profile being the Low-DY portfolio.
- Portfolios sorted according to liquidity have a more favourable correlation profile for actively traded stocks (High-Volume), than lesser traded stocks (Lower-Volume). However, larger standard deviation moves towards the downside result in a more of a asymmetric shape for more actively traded stocks than their lesser traded counterparts. For portfolios made up of actively traded stocks, symmetry either side of the mean holds for small standard deviation moves. However as standard deviation is increased the positive and negative tails do not follow similar patterns and become asymmetric. For the left tail the Low-Volume portfolio has a more favourable correlation profile than the High-Volume portfolio as it tracks the market less for downside moves. For the right tail, the High-Volume has a more favourable correlation profile than the Low-Volume portfolio.

1.8 CONCLUSION AND STRUCTURE OF DISSERTATION

As previously mentioned, an extensive body of research already exists for style factors in South Africa. The broad foundation of documented studies on the explanatory power of style factors on the JSE is well established to motivate local researchers to shift their “crosshairs” onto a new body of research by using these previous findings. The existing body of research on style factors can be evaluated by using a conditional correlation overlay. This will concentrate the attention onto the correlation between the style portfolio and the market portfolio for standard deviation moves of equal size either side of its respective mean. The research objectives will conclude by uncovering the nature of the symmetry present in portfolios constructed according to style and document any anomalies apparent in the individual style sub-portfolios.

Chapter Two literature review will open with a general summary of capital market theories and then move onto separately investigate the core matters of this study, namely, style portfolio characteristics and asymmetric correlations. The body of literature relating to style factors will focus on both developed countries and South Africa. The later part of the literature review will focus on asymmetric correlation studies under extreme market conditions. The chapter will conclude as a good foundation for investigating correlation symmetry whilst using style attributes as a proxy for the actively managed portfolio.

Chapter Three will consider the research design and method to accurately measure the degree of symmetry of the correlation profiles of style portfolio and market portfolio. This will be carried out by using select standard deviations either side of their respective means. The piecewise linear regression and the GARCH-M model are both motivated and considered as techniques to measure correlations that are conditioned at a chosen exceedance (standard deviation) levels. It is determined that the GARCH-M model is the most appropriate model to use over the 10 year study period.

Chapter Four provides the results and analysis of each style factor across the full 10 year. The null hypothesis of correlation symmetry is tested across the differing portfolios constructed according to the following styles: large versus small, high PE versus low PE, high dividend yield versus low dividend yield and actively traded versus thinly traded stocks. These asymmetries are measured at exceedance levels 0.1, 0.5, 1.0 and 1.5.

Chapter Five concludes with a revisit to the objective of the study, a summary of the implications of the findings and a suggestion for future research.

1.9 LIST OF ACRONYMS

The list of acronyms used through the course of this paper:

Table 1-1: Acronyms

AMEX	American Stock Exchange
APT	Arbitrage Pricing Theory
ARCH	Autoregressive Conditional Heteroskedasticity
B/P	Book value per share / price per share
BE	Book value equity
BoE	Bank of England
BoJ	Bank of Japan
BTM	Book-to-Market
CAPM	Capital Asset Pricing Model
CCC	Constant Conditional Covariance
DCC	Dynamic Conditional Correlation
DJ	Dow Jones
DJIA	Dow Jones Industrial Average
DY	Dividend yield
ECB	European Central Bank
EMH	Efficient Market Hypothesis
FE	Fixed Effects
GARCH	Generalised Autoregressive Conditional Heteroskedasticity
GARCH-M	GARCH-in-mean
GLM	Generalised Linear Model
HML	High-minus-low
IAS	International Accounting Standards
IFRS	International Financial Reporting Standards
JET	Johannesburg Equity Trading
JSE	Johannesburg Securities Exchange
ME	Market value equity
MPT	Modern Portfolio Theory
MSCI	Morgan Stanley Capital International
NAV	Net asset value
NYSE	New York Stock Exchange
OPEC	Organization of Petroleum Exporting Countries
PLR	Piecewise Linear Regression

QE	Quantitative Easing
RE	Random Effects
S&P	Standard and Poors
SLB	Sharpe-Lintner-Black
SMB	Small-minus-big
TSE	Tokyo Stock Exchange
UK	United Kingdom
US	United States
VAR	Value at Risk

CHAPTER TWO

LITERATURE REVIEW

2.1 INTRODUCTION

This chapter starts by exploring Capital Market Theories under section 2.2, beginning with early work by Markowitz on expected return versus variance and then moves onto the establishment of the efficient frontier which later became known as Modern Portfolio Theory (MPT). This is followed by an up to date discussion of the Capital Asset Pricing Model (CAPM) and Arbitrage Pricing Theory (APT) theories, followed by a short review of the Efficient Market Hypothesis (EMH) accompanied by context to this study. This chapter continues by building the case for the use of style portfolios combined with conditional correlations in the proposed study. Style effects will be covered under section 2.3 with section 2.3.2 focusing on style findings in developed markets and section 2.3.3 summarising South African market findings. Section 2.3.3 has an emphasis on South Africa and concentrates on individual style effects and their respective empirical evidence. After the literature basis of style effects has been established, section 2.4 will proceed to round up previous international theory and empirical findings relating to conditional correlations asymmetries.

2.2 CAPITAL MARKET THEORIES

Markowitz (1952) revolutionised portfolio management by attributing a value to the risk relative to an investment decision. The assumption was made that investors seek to maximise returns and are also risk averse as they seek to minimise risk. Investment managers and economists of the past were always aware of taking both risk and return into consideration, but risk was previously discussed in general terms and was based more on feeling and intuition. The study was able to quantify this "undesirable thing" that investors were trying to banish from their portfolios and was able to capture risk and articulate it mathematically through an expected return and variance trade-off model.

The model reduced an investor's portfolio to balancing two dimensions, namely the expected return of the portfolio and the portfolio's variance or standard deviation. Markowitz (1952) convinced investors to be equally concerned with the volatility or risk of investments as they are, with the return of investments. The paper demonstrated that the risk of a diversified portfolio depends not only on the individual variance of return of the individual assets making up a portfolio, but also their correlation that is their interaction amongst themselves and the overall influence on return, more precisely – the opposite movement of all assets, when one asset class goes up, another goes down. Assets no longer began to be considered in isolation when constructing a portfolio, but more on their overall contribution to the variance of the portfolio as a whole.

Using several stocks from the New York Stock Exchange (NYSE), Markowitz (1952) created the first efficient frontier combining these risky assets with a riskless asset: cash. The efficient frontier consisted of a curve which identified a series of optimal portfolios. These portfolios on the curve maximised the return for a given level of risk. It offered one of two options: the investor can select the highest expected return for any given level of risk, or the lowest level of risk for any given expected return. This approach became known as Modern Portfolio Theory (MPT) and presented an optimized selection of portfolios by maximising the investor's return per unit of risk.

The Capital Market Line through Tobin (1958) was added to the MPT and extended Markowitz's early work. The work distinguished MPT by expanding the investment universe from just shares, being a single asset class, to include multiple asset classes. In this early work the additional asset class was considered liquid and as near cash as possible, namely Treasury Bills. This helped the original model move away from a series of best portfolios to one optimal portfolio for everyone, the market portfolio. The investor was able to split the portfolio across Treasury Bills and the market portfolio. If the investor wanted to increase their expected return the percentage combination of risky assets, common stocks, was increased. By adjusting this ratio of risky assets to riskless assets, the investor can maximise their return relative to the risk incurred.

Markowitz (1952) used the standard deviation of a portfolio's returns as the appropriate measure of risk. The basic theory available to describe the influence of investor preferences on the price of risk was correlation and the physical attributes of individual stocks could be used by combining stocks that are negatively correlated. It was known that through diversification some of the risk inherent in a stock could be avoided, but very little was known of the actual risk component which was relevant. Sharpe (1964) demonstrated that a stock portfolio's risk can be categorised into two parts: an unsystematic component that can be diversified away and a systematic component that cannot be further reduced through diversification. During this period in the 1960s Sharpe (1964), Lintner

(1965), Mossin (1966) and Black (1972) were all independently working on a model which later became known as the CAPM.

Diversification has been at the centre of finance for over 50 years and to paraphrase Markowitz (1952), diversification is the only free lunch in finance. Much effort has gone into developing modern portfolio theory within the Markowitz mean-variance framework. Perhaps foremost amongst those efforts is the CAPM developed by Sharpe (1964). The CAPM measures the amount of return that a portfolio had to earn in order to fairly compensate the investor for the risk incurred. The model is a theory of what can be inferred about expected returns when markets are in equilibrium, homogenous expectations prevail combined with all investors seeking a mean-variance optimal. Under this regime, Sharpe (1964) was the first author to construct a market equilibrium theory of asset prices under conditions of risk as the basis of a model for the determination of capital asset prices. The theory reinforced the belief that diversification allowed the investor to escape all risk but not that resulting from the expansions and contractions of economic activity. The main point of consideration at the time was the response of a stock's rate of return to the presiding level of economic activity.

The invent of the CAPM model represented an important milestone in financial economics as it is an early single-factor model of the asset price, where beta is exposed to changes in value of the market. However the CAPM beta is insufficient to capture all the systematic risk. The CAPM model stopped short of defining these factors as it summed all those factors into beta. Ross (1976) with the introduced "other factors" at work besides beta but stopped short of defining these factors. Roll (1977) discussed the core failings of the CAPM which lead to the creation of the APT. The study firstly concludes that there is only a single testable hypothesis associated with the generalized two-parameter asset pricing model of Black (1972). This hypothesis is that 'the market portfolio is mean-variance efficient'. Secondly all other so-called implications of the CAPM model, the best known being the linearity relation between expected return and beta, follow from the market portfolio's efficiency and are not independently testable. This debunks the CAPM model as it is based on the 'if and only if' relation between return/beta linearity and market portfolio mean-variance efficiency.

The arbitrage model was proposed as an alternative to the mean variance CAPM as the theoretical grounds underpinning the CAPM, that of normality of returns to guarantee such efficiency were difficult to justify. The ignorance surrounding the identities of "other factors" were later defined by

Chen, Roll and Ross (1986) as inflation, GNP and yield curves as significant factors in explaining share returns. This bridged the gap between the theoretically exclusive importance of systematic state variables and the economic variables responsible for these exogenous influences.

Over a 50 year sample period Fama and French (1992) conducted a study to determine whether CAPM, using only beta as a factor, could fully explain the expected return of stocks. The results were in contrast to CAPM's main premise and did not hold empirically over the 50 year sample period. The authors considered expanding the original single factor CAPM model by adding additional risk factors that had characteristics of outperformance, in attempt to adjust downwards for this outperformance. Their research found that value stocks outperformed growth stocks and similarly, small cap stocks outperformed large cap stocks. The intuition behind the inclusion of the size factor was that small companies tend to outperform large companies because they are in different stages of growth and the intuition for including the value factor was that stocks with high BE/ME (value stocks) tend to outperform low BE/ME stocks (growth stocks) because they are believed to be undervalued in the stock market. Hence by adding the risk factors of value and size to the market factor (beta), the CAPM became a three factor model and better adjusted for the outperformance tendency. The onset of this new model better explained the stock returns.

Fama and French (2004) conclude the version of the CAPM developed by Sharpe (1964) and Lintner (1965) has never been an empirical success. For example, finance textbooks often recommend using the Sharpe-Lintner CAPM risk-return relation to estimate the cost of equity capital. The prescription is to estimate a stock's market beta and combine it with the risk-free interest rate and the average market risk premium to produce an estimate of the cost of equity. The typical market portfolio in these exercises includes just U.S. common stocks. Their empirical work shows that the relation between beta and average return is flatter than predicted by the Sharpe-Lintner version of the CAPM. As a result CAPM estimates of the cost of equity for high beta stocks are too high (relative to historical average returns) and estimates for low beta stocks are too low (Friend and Blume, 1970). Similarly, if the high average returns on value stocks (with high book-to-market ratios) imply high expected returns, CAPM cost of equity estimates for such stocks are too low.

In the early empirical work, the Black (1972) version of the model, which can accommodate a flatter trade-off of average return for market beta, had some success. But in the late 1970s, research began to uncover variables like size, various price ratios and momentum that add to the explanation of average returns provided by beta. These problems are serious enough to invalidate most applications of the CAPM. Fama and French (2004) point out that the CAPM is often used to measure the performance of mutual funds and other managed portfolios. The approach from Jensen (1968) is to estimate the CAPM time-series regression for a portfolio and use the intercept (Jensen's alpha) to measure abnormal performance. The problem is that, because of the empirical failings of the CAPM, even passively managed stock portfolios produce abnormal returns if their investment strategies involve tilts toward CAPM problems (Elton, Gruber, Das and Hlavka, 1993). For example funds that concentrate on low beta stocks, small stocks or value stocks will tend to produce positive abnormal returns relative to the predictions of the Sharpe-Lintner CAPM, even when the fund managers have no special talent for picking winners. Just briefly touching on the results discussed in chapter 4 of this JSE study, the Small firm and Low-PE portfolio (value stocks) produce returns that are lower for the positive tail than their Large firm and High-PE portfolio (growth stocks) counterparts. However it must be noted that the difference between this study and the Fama and French (2004) study is that they did not isolate the return data into exceedance levels. Instead their study focused on unconditioned samples. This does take away from the results slightly but the comparison still yields results that show there is a difference in diversification between the two studies.

The CAPM while brilliant in its simplicity and clarity, but is questionable whether the assumptions upon which the model depends reflect real market conditions and whether its conclusion can be transposed to actual portfolio management [Ross, 1976; Chen, Roll and Ross, 1986]. A separate set of arguments are concerned with the dynamic aspects of portfolio construction. Accounting for dynamic changes in the portfolio has led to an examination of these dynamic changes as a source of return. Fernholz and Shay (1982) stated that constant-proportion portfolios earned additional returns over the returns earned by buy-and-hold portfolios. Booth and Fama (1992) described these additional returns as diversification returns. Although they provide useful insights, the different examinations of multi-period rebalancing effects are not directly useful for portfolio construction because they only deal with portfolio dynamics after the original weights have been decided.

Although very useful in describing and understanding portfolio construction issues, the mean-variance framework has some practical problems. As pointed out by Choueifaty and Coignard (2008) whilst variance can be estimated with a fair level of confidence, returns are so much more difficult to estimate that the most popular models (CAPM and Black-Litterman) have in one way or another completely put them aside. It is now become increasingly popular to claim that the market capitalization-weighted indices are not efficient. Several alternative empirical solutions have been suggested, such as fundamental indexation and equal weights. The researchers investigate the theoretical and empirical properties of diversification as a criterion in portfolio construction on the Standard & Poors (S&P) 500 Index and the Dow Jones (DJ) Euro Stoxx Large Cap Index data from December 1990 to February 2008. They compare the behaviour of the resulting portfolio to common strategies, such as market cap-weighted indices, minimum-variance portfolios and equal-weight portfolios. They consider a diversification ratio which is the ratio of the weighted average of volatilities divided by the portfolio volatility. A portfolio which maximizes the diversification ratio from the available stock universe is denoted as the Most-Diversified Portfolio.

When estimating the covariance matrix the researchers note that it is important to examine the impact of estimation errors on the resulting portfolio. It is noted that there are a variety of ways to estimate covariance such as decayed weighting, GARCH, and Bayesian update methodologies. Estimation errors often occur at the levels of volatility and correlation, however the hierarchies of correlations prove to be more stable. It is documented that portfolios built using differently estimated covariance matrices have similar characteristics. Also changing the frequency of data and the estimation period has little impact on the final results. Even portfolios that are built on forward-looking covariance matrices (having perfect covariance foresight) have only slight differences in results than when using historical covariance. The limited estimation errors between the different methods employed on the covariance matrix is a comforting finding for this JSE correlation study.

The result of the empirical tests for the portfolios is that the Most-Diversified Portfolio consistently delivers superior risk-adjusted returns in both regions (S&P and DJ) compared to the minimum-variance portfolio, equal-weight portfolio and the market cap-weighted index. It is also consistently less risky than the market cap-weighted indices (the volatility is 13.9% versus 17.9% for Eurozone equities and 12.7% versus 13.4% for U.S. equities).

The results show that market cap-independent methodologies tend to be less biased toward large capitalizations than market cap-weighted indices. Therefore, a comparison of the Most-Diversified Portfolio to market capitalization weighted indices should always show a similar size bias. To measure the importance of factor bias in the empirical results, a three-factor Fama and French regression was performed [Fama and French, 1993,1996] on the performance of the portfolios versus the market, HML (high-minus-low book value), and SMB (small-minus-big capitalization) factors. The results indicate that the dominant factor explaining the outperformance over the period is specific risk, meaning that about 18% (out of 48%) of the outperformance cannot be explained by the predefined factors of the model. This performance arises from real stock specific risk, omitted common risk factors and changes in exposure to factors.

Choueifaty and Coignard (2008) determine the assumptions that may explain the reason that the Most-Diversified Portfolio is better (in terms of Sharpe ratio) than the market cap-weighted benchmark. Firstly although the Most-Diversified Portfolio is ultimately very different from the benchmark, the implied expected returns from the Most-Diversified Portfolio are not very different from those of the market cap-weighted benchmark. Actually the only difference resides in the "correct pricing" of individual assets' correlations to the benchmark. In other words, the correlations (with the market) need to be only partially taken into account by the market when securities' prices are determined. Now it is important to explain why this would be the case in the real world. The following assumptions are consistent with a market environment that could explain the dominance of the Most-Diversified Portfolio over market-cap indices. Firstly investors are rational and all else being equal, if a security has a higher volatility, investors expect a higher return. Secondly the market has enough efficiency to prevent arbitrage opportunities at the single-stock level - security prices reflect all public information; in other words, securities are correctly priced on a stand-alone basis. Thirdly forecasts of volatilities are accurate. Fourthly all other forecasts are either inaccurate or not taken into account in the pricing of securities. However the researchers admit that these assumptions alone are not enough for the Most-Diversified Portfolio to be an equilibrium model.

The goal of the Most-Diversified Portfolio is not to be an equilibrium model. It can, however, potentially be transformed into an equilibrium model either by adding additional assumptions or by adding fundamental valuation criteria such as earnings and sales. Such additions would allow the model to accommodate different miss-pricings. Choueifaty and Coignard have defined a portfolio construction methodology that can be considered as an alternative to other nonmarket-cap benchmarks. It is a new investment style that favours diversification and avoids bets based on return prediction or confidence in the implicit bets of market cap-weighted benchmarks.

Egozcue, Garcia, Wong and Zitikis (2011) study the rankings of completely and partially diversified portfolios and also of specialized assets when investors follow so-called Markowitz preferences (Markowitz utility curve). The research focuses on addressing portfolio diversification when investors possess Markowitz utility functions. Drawing from von Neuman and Morgenstern (1944), their expected utility theory is based on the assumption that utility functions of risk-averse and risk-inclined investors are concave and convex, respectively; both are increasing. When examining the relative attractiveness of various forms of investments, Friedman and Savage (1948) observed that concave utility functions may not be best for explaining why investors buy lottery tickets or insurance. Markowitz (1952) addressed this concern by suggesting utility functions with convex segments on both the positive and the negative parts of the real line. Specifically, on the negative real half-line, the functions are initially convex and then concave, and then on the positive real half-line, they are convex and finally concave. Thus, the utility functions have three inflection points, with one of them being located at 0, which Egozcue et al (2011) call the status quo throughout their paper as it serves the borderline between losses and gains.

Egozcue et al (2011) consider utility functions that are convex for gains and concave for losses - referred to as Markowitz utility functions. Also investors possessing Markowitz utility functions are referred to as “Markowitz investors”. The researchers have developed a theoretical study that aids in explaining the attitudes of Markowitz investors toward risk, including their preferences for specialized, partially diversified and completely portfolios. It turns out that diversification strategies for Markowitz investors are more complex than in the case of risk-averse and risk-inclined investors. In particular, it is observed that for Markowitz investors, preferences toward risk vary depending on their sensitivities toward gains and losses. The results show that unlike in the case of risk-averse and risk-inclined investors, Markowitz investors might in fact prefer investing their entire wealth in just one asset. This finding helps better understand some financial anomalies and puzzles, including the well-known diversification puzzle (Statman, 2004) which notes the tendency of some investors not to completely diversify investments and choose investing only in a few assets.

In relation to this JSE study, utility functions were not considered however an optimal diversification strategy was followed in the sense that sub-portfolios were created from the entire population of shares on the JSE (minus any shares that did not qualify past the thin trading filter). The sub-portfolios were created on an equal weighting similar to the approach considered by Choueifaty and Coignard (2008).

<u>*Efficient Market Hypothesis (EMH)*</u>

Advocates of the EMH require that investors and agents of the market have rational expectations: On average, the population would have the same information, leading to the same decisions. As new relevant information appears, the agents update their expectations appropriately. The main requirement of EMH is for investors' reactions to be random and follow a normal distribution pattern so that the net effect on market prices cannot be reliably exploited to make an abnormal profit. This study will make use of style factors which various studies of the past have shown to yield abnormal returns, making them anomalies of the EMH theory.

The theory of MPT has many attributes that can be considered for effectively managing an investment portfolio ranging from: the use of the expected return versus variance maxim (Markowitz, 1952); the selection of optimal portfolios through the efficient frontier (Markowitz, 1952) and capital market line (Tobin, 1958); the reliance on beta as a proxy for market risk (Sharpe, 1964) to the pricing of financial assets through the use of CAPM.

A seminal paper on the EMH by Fama (1970) notes that the theory of efficient markets is concerned with whether prices at any point in time "fully reflect" available information. The author argues that all of the available empirical literature at the time of the study was implicitly or explicitly based on the assumption that the conditions of market equilibrium can be stated in terms of expected returns. This assumption is the basis of the expected return efficient markets model. The empirical work documented in the paper can be divided into three categories depending on the nature of the information subset of interest. Strong-form tests are concerned with whether individual investors or groups have proprietary access to any information relevant to price formation. Fama (1970) concedes that such an extreme model would not be an exact description of the world, and it is probably best viewed as a benchmark against which the importance of deviations from market efficiency can be judged. The less restrictive semi-strong-form tests the information subset of interest and includes all obviously publicly available information, while the weak form tests the information subset which is just historical price or return sequences.

Fama (1970) documents results from the weak form test that are strongly in support of this model however there is also statistically significant evidence for dependence in successive price changes. It is argued that this is consistent with the "fair game" model and therefore does not appear to be sufficient to declare the market inefficient. Also for price changes or returns covering a day or longer, there is little evidence against the random walk. Thus it is concluded that there is consistent evidence of positive dependence in day-to-day price changes and returns on common stocks, and the dependence is of a form that can be used as the basis of marginally profitable trading rules. The dependence shows up as serial correlations that are consistently positive but also consistently close to zero, and as a slight tendency for observed numbers of runs of positive and negative price changes to be less than the numbers that would be expected from a purely random process.

Evidence in contradiction of the "fair game" efficient markets model for price changes or returns covering periods longer than a single day are rare and difficult to find in the study. There is evidence of dependence in returns which provides interesting insights into the process of price formation in the stock market, but it is not relevant for testing the efficient markets model. For example, the results show that large daily price changes tend to be followed by large changes, but of unpredictable sign. This suggests that important information cannot be completely evaluated immediately and that the initial first day's adjustment of prices to the information is unbiased.

Fama (1970) shows that the semi-strong form tests in which prices are assumed to fully reflect all obviously publicly available information also support the EMH. Thus Fama, Fisher, Jensen and Roll (1969) find that the information in stock splits concerning the firm's future dividend payments is on average fully reflected in the price of the split share at the time of the split. Ball and Brown (1968) also come to a similar conclusion with respect to the information contained in the annual earnings announcements of firms and the new issues and large block secondary issues of common stock.

The strong-form efficient markets model, in which prices are assumed to fully reflect all available information is viewed as a benchmark against which deviations from market efficiency can be judged. Such deviations have were observed by Niederhoffer and Osborne (1966) that firstly point out that specialists on major security exchanges have monopolistic access to information on unexecuted limit orders and they use this information to generate trading profits. This raises the question of whether the market making function of the specialist could not be carried out by some other mechanism that does not imply monopolistic access to information. Secondly, Scholes (1969) finds that corporate insiders often have monopolistic access to information about their firms. The studies note that corporate insiders and specialists are the only two groups whose monopolistic access to information has been documented. There was no evidence that deviations from the strong form of the EMH model permeate down any further through the investment community. Hence for the purposes of most investors Fama (1970) concludes that the EMH model seems a good first approximation to reality.

In recent years, many financial economists have come to question the EMH. At least on an ex-post basis there seem to be several instances where market prices failed to reflect available information. For example the period of large-scale irrationality known as the internet "bubble" of the late 1990s extending into early 2000, have convinced prominent analysts [such as Shiller (2000)] that the efficient market hypothesis should be rejected. In addition, financial econometricians have suggested that stock prices are, to a significant extent, predictable on the basis either of past returns or of certain valuation metrics such as dividend yields and PE ratios [Fama and French (1993)].

Malkiel (2005) notes that although it is possible to cast doubt on the statistical robustness of many of the predictable patterns that have been suggested [Fama (1998)] the researcher's scepticism is based on somewhat different evidence. The study is conducted over a 30 year period from 1972 to 2002 on the U.S market. The theory is based on the fact that if market prices often fail to reflect rational estimates of the prospects of companies and if markets consistently overreact (or under-react) to underlying conditions, then professional investors should be able to produce excess returns. The strongest evidence suggesting that markets are generally quite efficient is that professional investors do not beat the market with close to three quarters of the mutual funds holding large capitalization stocks were outperformed by the (large capitalization) Standard and Poor's (S&P) 500 stock index. When returns are measured over periods of 10 years or longer, over 80% of active managers are outperformed by the index.

The evidence accumulated by this study from the S&P 500 over the past 30-plus years may indicate that the U.S. stock markets are remarkably efficient at adjusting correctly to new information. If prices were often irrational and if market returns were as predictable as some critics of the efficient market hypothesis believe, then it should be possible for actively managed investment funds to outdistance a passive index fund that simply buys and holds the market portfolio. Although it is true that in any period there are some active managers who do achieve returns higher than the index, it is not possible to tell in advance who they will be. There is not sufficient persistence in performance to be able to choose winning managers by an examination of their past records. Interestingly the 10 best actively managed funds during the 1960s achieved rates of return almost double that of the index but those same funds underperformed the index during the decade of the 1970s. Similarly, the best funds of the 1970s underperformed during the 1980s and the winners of the 1980s achieved below average returns during the 1990s.

Index funds tend to outperform actively managed funds in international as well as in domestic markets. The findings over the same 30 year period show evidence of that actively managed European equity funds underperform the Morgan Stanley Capital International (MSCI) Europe stock market index. While in many individual years, 50% or more of the active managers do beat the index, however the longer-term results confirm the paper's same findings for the United States. Over a 10-year period ending December 31, 2002, over 80% of the actively managed funds underperformed the index.

The evidence appears to point to the conclusion that active equity management is, in the words of Ellis (1998), a "loser's game." Switching from security to security may accomplish nothing more than to increase transactions costs and harm performance. Thus, even if markets are less than fully efficient, indexing is likely to produce higher rates of return than active portfolio management.

Regarding this specific style factor study of the JSE, it is not the intention to determine the market's level of efficiency but in the same token if it can be shown that certain sub-portfolios outperform others by tracking the market more closely than others. This on its own can provide an argument that the JSE is not perfectly efficient. However this study will only focus on the correlation aspect of MPT and will not explore the whole theory of diversification. The theory of portfolio construction and other accompanying aspects will not be borrowed from MPT as style portfolios will be used as a portfolio construction method.

2.3 STYLE EFFECTS IN DEVELOPED AND DEVELOPING MARKETS: EMPIRICAL EVIDENCE

2.3.1 <u>Introduction</u>

The usefulness of style characteristics as a predictor of returns has been tested extensively in a capital market perspective since the 1950s. The basic research framework followed in these capital market studies involves using stock factors as explanatory variables in modelling the concurrent revisions in stock prices. For each style effect the relevant literature has been reviewed through its own chronological development along broad methodological classifications. These are summarised in tables at the beginning of each style effect section.

2.3.2 <u>Style effects in international markets</u>

The asset-pricing model of Sharpe (1964), Lintner (1965), and Black (1972) shaped the early landscape for the way market participants thought about average returns and risk. The central prediction of the model is that the market portfolio is mean-variance efficient in the sense of Markowitz (1958). The efficiency of the market portfolio implies that the expected returns of securities are a positive linear function of their market betas (the slope in the regression of a security's return on the market's return), and that the market betas suffice to describe the cross-section of expected returns. This paradigm then shifted once key research discovered share returns could be better explained by using other factors.

The ranking of shares according to the nominated style is the backbone to the explanatory power of the multifactor model. It allows shares to be isolated into precise categories before a factor model is applied to explain returns. Black (1973) was one of the first to develop the Value Line system for ranking securities into five groups. On a two parameter model and risk-adjusting the returns, the results earned by rank 1 stocks bettered rank 5 stocks 70% of the time. A possible key to this phenomenon could be the fact that rankings are based upon the shares' earnings and dividend yields and changes in earnings yields. In summary the Value Line system tendered to assign high ranks to stocks with low PE ratios relative to historical norms and relative to PE ratio of the market. The discovery of these factors lead to empirical contradictions of the Sharpe-Lintner-Black (SLB) model. Research then began to branch out and investigated possible factors that could better explain share returns.

<u>Size effect</u>

Table 2-1: Summary of size empirical studies reviewed

Authors	Year	Classification
Banz	1981	Early discovery of the size effect; CAPM contradiction
Reinganum	1981	Early size effect documented
Brown, Kleidon and Marsh	1983	Size effect documented
Keim	1983	Size effect; small firms have high betas
Kato and Schallheim	1985	Presence of size effect in Japan
Lamoureux and Sanger	1989	Size effect; small firms have lower betas
Chan, Hamao and Lakonishok	1991	Size effect in Japan
Fama and French	1992a	Size effect; no relation between beta and returns; CAPM contradiction
Fama and French	1993	Size effect arises endogenously due to systematic risk
Fama and French	1995	Theoretical explanation for size effect
Berk, Green and Nail	1999	Addressed the critique size effect is not founded on economic fundamentals
Vassalou and Xing	2004	Disappearance of size effect
Acharya and Pedersen	2005	Small firm sensitivity to liquidity
Petkova	2006	Disappearance of size effect
Hwang, Min, McDonald, Kim and Kim	2010	Disappearance of size effect
Easterday, Sen and Stephan	2009	Size effect arbitraged away due to market efficiency
Van Dijk	2011	Summary of all previous work done on the size effect and research shortcomings– concludes it is premature to argue the extinction of size effect

One of the most prominent factors discovered creating the contradiction is the size effect of Banz (1981). The research uncovered compelling evidence of a size effect on the U.S. stock market and is among the first observed empirical contradictions of the CAPM. The paper analyses all common stocks listed on the NYSE between 1936 and 1975. The study concluded that a portfolio made up of small firms outperform a similar portfolio of large firms. Evidence in the empirical research indicated that shares of firms with large market values have had smaller returns, on average, than similar small firms. It was noted that stocks in the quintile portfolio with the smallest market capitalization earn a risk-adjusted return that is 0.40% per month higher than the remaining firms. The Fama and MacBeth (1973) regressions were also run on the data and show a negative and significant relation between returns and market value. The size effect is not linear and is most pronounced for the smallest firms in the sample. On average, the risk-adjusted returns of small NYSE firms are significantly higher than large NYSE firms. The findings concluded that market equity, ME (a stock's price times shares outstanding), adds to the explanation of the cross-section of average returns provided by market betas. The average returns on small stocks are too high given their beta estimates, and average returns on large stocks are too low. A theory was proposed that small firms outperform large firms as investors may not want to hold smaller firms as insufficient information is available for this subset of shares resulting in estimation risk.

Reinganum (1981) analyses the size effect in a sample of 566 NYSE and Amex firms over the period 1963–1977. The findings are that the smallest size decile outperforms the largest by 1.77% per month. Brown, Kleidon and Marsh (1983) re-examine the size effect using the Reinganum (1981) data and conclude that there is a linear relation between the average daily return on 10 size-based portfolios and the logarithm of the average market capitalization. Keim (1983) in a study on NYSE and Amex firms over the period 1963–1979 reports a size premium of no less than 2.5% per month in a broader sample of. Also it is shown that small firms have higher betas than large firms, but the difference cannot fully explain the return differential. Based on 20 size-sorted portfolios over the period 1973–1985, Lamoureux and Sanger (1989) find a size premium of 2.0% per month for NASDAQ stocks and of 1.7% for NYSE/Amex stocks. They also document that small firms have a lower beta than large firms on NASDAQ.

Although various important contributions appeared in the 1980s after the original work by Banz (1981), research on the size effect gained strong momentum after the appearance of Fama and French (1992a) paper. They examined the size and BTM anomalies uncovered by earlier studies and make the case that the empirical shortcomings of the CAPM of Sharpe (1964) and Lintner (1965) are simply too important to be ignored. Using a sample of NYSE, Amex, and NASDAQ stocks over the period 1963–1990, Fama and French find that the smallest size decile outperforms the largest decile by 0.63% per month. Also when they rank each size decile into 10 beta-sorted portfolios, they find no relation between beta and returns. Also Fama–MacBeth regressions confirm that beta does not help to explain the cross-section of returns - rather size and BTM have more significant explanatory power.

Size effects are also present on the Japanese stock market and results[1] indicate sensitivity towards the chosen market index. A further finding is the remarkable similarity of the size anomaly between the U.S. and Japanese stock markets. This similarity may have been indicative of the well-integrated markets on an international scale.

During this period there was very limited research available on style effects in the Japanese market after Kato and Schallheim (1985) with much of the research being focused on the U.S. until Chan, Hamao, and Lakonishok (1991) attempted to draw parallels between findings in a Japanese context to American data in terms of a size and BTM effect. In order to fill this research gap, the paper related cross-sectional differences in returns of Japanese stocks on the Tokyo Stock Exchange (TSE) to the behaviour of the variables: earnings yield, size and cash yield. The motivation is to ascertain whether the same factors are at work in the two countries and use this to further strengthen the study's findings in the U.S. The findings reveal a significant cross-sectional relationship between the chosen variables and the expected returns in the Japanese market.

Easterday, Sen and Stephan (2009) examine whether the small firm effect has declined over time due to market efficiency. The study documents that the small firm effect persists over a long period of time (1946-2007) and has not been arbitraged away. NASDAQ listed firms are also studied and are compared across all three major U.S. trading exchanges. Their main hypothesis is the correlation between returns and trading volume for small firms is greater in December and January than in other months.

Their investigative approach utilizes simple intuitive regression models and monthly trading volume and returns data are used to mitigate the problems encountered by Lakonishok and Smidt (1984) in calculating daily returns for thinly traded firms. Their premise is that investors are attempting to arbitrage the January which may affect also influence December trading behaviour, so January (December) observations are excluded from the regression equation. The regression samples are restricted to the smallest firms in order to focus on the association between returns and

[1] See findings of Kato and Schallheim (1985)

trading volume for firms in which the January effect is most prevalent. They also suspect that if long positions established in December are reversed in January to capture the returns, then trading volumes in December and January should be more highly correlated than in January and February, February and March. The hypothesis is therefore: the correlation between December and January trading volume for small firms is higher than for other consecutive pairs of months.

The findings illustrate for the small firm/January effect for firms trading on NYSE and American Stock Exchange (AMEX) during three broad outcomes. The January premium for small firms is larger than the premium for any other month; the January premium decreases with firm size and the February–December premiums are relatively flat across all firm size deciles. The researchers also wanted to review this anomaly of the small firm/January effect on the NASDAQ as this anomaly has been documented in mature markets such as NYSE and AMEX and it would be worthwhile to understand if this anomaly had to suddenly appear in a new market characterized by different trading mechanisms. The NASDAQ market, started in 1971, was the world’s first electronic stock exchange. It grew rapidly and by 1994 more shares were traded on NASDAQ than on NYSE, although NYSE’s market capitalization still remains the largest in the US. The researchers believe if learning had taken place, one might expect the NASDAQ exchange to be free of the January effect since the anomaly was discovered and made public many years prior to the start of NASDAQ.

Eaterday et al (2009) show that this is not the case. The January value-weighted return premiums on the NASDAQ are significantly higher than those of other months and are correlated negatively with firm size. The small firm/January is clearly present in the NASDAQ exchange firms, and therefore this hypothesis is rejected. Having now established that the January effect occurs on NASDAQ, NYSE and AMEX, the next question is whether there are meaningful differences in the magnitude of the effect across these trading exchanges. The results conclude that AMEX firms have the highest premiums, while NYSE firms have the lowest and NASDAQ firms generally fall between the two extremes. These results suggest that there could be differences in January premiums that are driven by the trading exchanges.

Van Dijk (2011) notes a remarkable paradox that has developed since the 1990s in research on the size effect. The objections against the lack of theory behind risk-based explanations for the size effect resulted in the development of several theoretical models in which the size effect arises endogenously as a result of systematic risk (Fama and French, 1993; Fama and French, 1995). On the other hand, empirical research suggests that the size effect has disappeared since the early 1980s

(Vassalou and Xing, 2004; Petkova, 2006; Hwang, Min, McDonald, Kim and Kim (2010), According to van Dijk (2011) this paradox has brought a halt to research on the size effect.

The paper argues that it is premature to conclude that the size effect has gone away as stock returns are very noisy and standard errors around estimates of the size premium are large therefore it is difficult to conclude whether the size effect is larger or smaller than it used to be. Secondly although the theoretical explanations offered for the size effect is potentially valuable, whether and how existing models can be reconciled with known patterns in the returns on small and large stocks is not clear. In particular, there is a need for more empirical and theoretical research to evaluate the extent to which theories based on firm-level investment decisions, stock market liquidity, and investor behaviour can explain the size effect.

Berk, Green and Naik (1999) addressed the critique that the risk-based explanations of the size effect are not founded on economic theory that identifies the state variables that drive variation in returns related to firm size. The paper analyses firm-level investment decisions in models in which the relation between firm size and stock returns arises endogenously. In the model the dynamics of a firm's systematic risk and its expected returns are related to the size and the book-to-market ratio of the firm and the model predicts that time-series and cross-sectional variation in stock returns can be explained by market value. Simulations based on this model perform reasonably well in generating empirical patterns similar to those detected by Fama and French (1992) however, empirical research that directly tests whether the patterns observed in the returns of small and large stocks are in line with the predictions of these models is essentially lacking.

Liquidity is also considered by van Dijk (2011) due to the fact that the returns of small firms are possibly sensitive to time-series variation in market liquidity. Beginning with Pastor and Stambaugh (2003) present evidence that systematic liquidity variation is a priced source of risk, but they also contend that the relation between liquidity risk and firm size is not straightforward. However they do not investigate whether size is a significant determinant of expected returns after correcting for liquidity risk. Acharya and Pedersen (2005) show that the expected return on a stock depends on its expected liquidity and on the covariance of its own return and liquidity with the market return and liquidity. Their cross-sectional tests show that the model has a higher explanatory power than the CAPM, and that the liquidity risk premia are economically significant. Their liquidity risk factors improve the fit for portfolios of small stocks, but Acharya and Pedersen (2005) do not examine whether liquidity risk absorbs the size effect either.

Van Dijk notes that explanations for the size effect based on economic theory are essential for the understanding of the effect. Both sorting procedures and cross-sectional tests are vulnerable to data mining and because market value and firm risk are inversely related, size will pick up any omitted risk factor in asset pricing tests. Around the time of publication of the first papers that suggest that the size effect has disappeared in the U.S., several new research initiatives started to address this deficiency. He summarises three promising strands of theoretical literature. Firstly, models of firm-level investment decisions generate an endogenous relation between firm size and stock returns. Berk et al. (1999) presented evidence that these models can reproduce several well-known features of stock returns. According to van Dijk this body of research is still in a relatively early stage and it is not sufficiently clear to what extent these models can explain patterns uncovered by empirical research on the size effect. Secondly, asset pricing models predict that stock returns not only depend on transaction costs, but also on liquidity risk. The evidence examined indicates that liquidity is an important factor in asset pricing. However, these studies do not explicitly examine whether the size effect can be explained by liquidity factors. How the size effect and liquidity interacts is potentially an important area for future research. Thirdly, the size effect can be the behaviour of less than fully rational investors, in the sense that either these investors may prefer assets with specific characteristics or that size (market value) proxies for the mispricing that their behavioural biases cause.

Van Dijk argues that the conclusion that the size effect has gone away is premature. In fact, he points out that the size premium in the U.S. has been positive and large in recent years. He notes the need for more empirical research to examine the robustness of the size effect on U.S. and international equity markets. There is very little known about the shifts in the size premium in the past few decades. At the same time, theories that could have potentially provided explanations for the size effect have neither been sufficiently developed nor systematically tested. New research may break the current deadlock in an area of literature that has important implications for the understanding of asset pricing, performance evaluation, and cost of capital estimation.

With the early discovery of the size effect by Banz (1981) and the numerous additions to it by Fama and French in the 1990s, looking back it was probably safe to conclude at that time that the size effect had cemented itself in international finance literature as a permanent stock market anomaly. However research presented under this section from the 2000s largely disputed its very existence and argued that it had completely disappeared. Fighting back in a summary paper Van Dijk (2011) argued it was premature to call the end of the size effect. In conclusion based on these recent findings it is still a valuable facet of style research which will be important cornerstone of this study.

Value effect

Table 2-2: Summary of value empirical studies reviewed

Authors	Year	Classification
Jones	1973	Early discovery of the value effect
Black	1973	Developed the Value Line System
Basu	1977	Possible explanation for value effect is investor expectation of future performance
Ball	1978	Value ratios used as proxy for yield surrogates
Basu	1983	E/P ratio explain returns in tests including beta and size
Chan and Chen	1991	Risk captured by value is possibly a relative distress factor
Fama and French	1992a	Return risk is dimensioned and proxied through value effect
Fama and French	1993	Develop a 5 factor model to explain returns whilst considering both stocks and bonds and
Griffin	2002	Examines whether country-specific or aggregate versions of Fama and French (1993) model better explain country returns
Karolyi and Stulz	2003	Integrated asset pricing across countries
Hou, Karolyi and Kho	2011	Value premiums across countries
Fama and French	2012	Examine models that use global factors to explain regional and global returns

The discovery of the value factor was also a prime catalyst that lead to the demise of the market beta as the best predictor of returns. In one of the earlier PE ratio studies conducted on the NYSE by Jones (1973) it is reported that the risk-adjusted profitability of strategies based on past earnings growth is improved by ranking securities on their past PE ratios. Preliminary evidence suggested that the stock market does not discount the earnings report instantaneously and instead the increased professional interest of the favourable earnings report is gradually disseminated through the market and consequently demand increases, driving up the share's price. Later studies conducted by Basu (1977) on shares on the New York Stock Exchange (NYSE) suggested that low PE portfolios earned higher absolute and risk-adjusted rates of return, on average, than portfolios consisting of randomly selected shares. A possible hypothesis for this relative outperformance is accredited to exaggerated investor expectations of future investment performance of high PE shares resulting in later ensuing disappointment. However unlike the test conducted for the size effect, whereby the returns for the small firms appear to be simultaneously accompanied by generally higher levels of variability (risk) this is clearly not the case for the high PE portfolios. Later, Ball (1978) focused a study on suitable variables as proxies for yield surrogates. The research was confined to earnings and dividend variables and emphasis was applied to risk control using a two-parameter model. The study accumulated evidence that the ratio of E/P is a strong proxy for unnamed risk factors in expected returns.

Basu (1983) showed that E/P helped explain the cross-section of average returns on U.S. stocks in tests that also include size and market beta. Ball's proxy argument for E/P was also applied to size, leverage, and book-to-market equity. All these variables are regarded as different ways to scale stock prices, to extract the information in prices about risk and expected returns (Keim, 1988). Moreover, since E/P and size are all scaled versions of price, it is reasonable to expect that some of them are redundant for describing average returns.

With the joint possibility of redundancy, and the possibility that beta could play a lesser role in the prediction of stock returns than originally thought, research began to focus on the key risk factors in the returns of stocks and bonds. Starting with Fama and French (1992a) their research goal was to evaluate the joint roles of market beta, size, E/P, leverage, and book-to-market equity in the cross-section of average returns on NYSE, AMEX, and NASDAQ stocks. Preceding research by Black, Jensen, and Scholes (1972) and Fama and MacBeth (1973) find that, as predicted by the Sharpe (1964), Lintner (1965), and Black (1972) **(**SLB model), there is a positive simple relation between average stock returns and beta during the pre-1969 period. Like Reinganum (1981) and Lakonishok and Shapiro (1986), the study finds that the relation between beta and average return disappears during the more recent 1963-1990 period, even when beta is used alone to explain average returns. The simple relation between beta and average return is also shown to be weak in the 50-year from 1941-1990 period. In short, their tests do not support the most basic prediction of the SLB model, that average stock returns are positively related to market betas. Unlike the simple relation between beta and average return, the univariate relations between average return and size, leverage, E/P, and

BTM are strong. In multivariate tests, the negative relation between size and average return is robust to the inclusion of other variables. The bottom-line results are that beta does not seem to help explain the cross-section of average stock returns, and secondly the combination of size and BTM absorb the roles of leverage and E/P in average stock returns, during the sample period 1963-1990. The researchers conclude that if assets are priced rationally, the results suggest that stock risks are multidimensional. One dimension of risk is proxied by size. Another dimension of risk is proxied by value through BTM or PE ratios. It is possible that the risk captured by value is the relative distress factor of Chan and Chen (1991). They postulate that the earning prospects of companies are associated with a risk factor in returns. Firms that the market may judge to have poor prospects, signalled by low stock prices and high ratios of BTM and low PE ratios, have higher expected stock returns (they are penalized with higher costs of capital) than firms with strong prospects. Whatever the underlying economic causes, their main result is straight forward - two easily measured variables, size and value, provide a simple and powerful characterization of the cross-section of average stock returns for the 1963-1990 period. Used alone, size, E/P**,** leverage, and book-to-market equity have explanatory power.

Focusing on the common risk factors to explain stock and bond returns Fama and French (1993) identify five common risk factors in the returns on stocks and bonds. They determine three stock-market factors: an overall market factor and factors related to firm size and BTM. There are two bond-market factors that are related to maturity and default risks. It is found that stock returns have shared variation between the stock-market factors and they are also linked to bond returns through shared variation in the bond-market factors. The bond-market factors capture the common variation in bond return, except for low-grade corporates. Importantly the five factors seem to explain average returns on stocks and bonds.

Interestingly the cross-section of average returns on U.S. common stocks shows little relation to either the market betas of the Sharpe (1964) - Lintner (1965) asset pricing model. Alternatively, variables that have no special standing in APT show reliable power to explain the cross-section of average returns. The list of empirically determined average return variables[2] includes size, E/P, leverage and BTM (value). This paper extends the asset-pricing tests in Fama and French (1992a) in three ways: Firstly it expands the set of asset returns to be explained. The only assets considered in Fama and French (1992a) are common stocks and if markets are integrated, a single model should

[2] See Banz (1981). Bhandari (1988). Basu (1983). and Rosenberg, Reid, and Lanstein (1985)

also explain bond returns. Fama and French (1993) include U.S. government and corporate bonds as well as stocks. Secondly, they also expand the set of variables used to explain returns. The size and BTM variables in Fama and French (1992a) were directed at stocks. They now extend the list to term-structure variables that are likely to play a role in bond returns. The goal is to determine whether variables that are important in bond returns help to explain stock returns, and vice versa. The idea is that if markets are integrated, there is likely some overlap between the return processes for bonds and stocks. Thirdly the approach to testing asset-pricing models is different as Fama and French (1992a) use the cross-section regressions of Fama and MacBeth (1973): the cross-section of stock returns is regressed on variables hypothesized to explain average returns. In the model's previous form it would be difficult to add bonds to the cross-section regressions since explanatory variables like size have no obvious meaning for government and corporate bonds. Instead they decide to use the time-series regression approach of Black, Jensen, and Scholes (1972). Monthly returns on stocks and bonds are regressed on the returns to a market portfolio of stocks and mimicking portfolios for size, BTM and term-structure risk factors in returns.

The interpretation of results, like the cross-section regressions of Fama and French (1992a), show that the time-series regressions of size and value factors can explain the differences in average returns across stocks. However these factors alone cannot explain the large difference between the average returns on stocks and one-month bills - this job is left to the market factor. In regressions that also include the size and BTM factors, all their stock portfolios produce slopes on the market factor that are close to 1. The risk premium for the market factor links the average returns on stocks and bills. In summary, their results suggest that there are at least three stock-market factors and two term-structure factors in returns.

When the excess market return is the only explanatory variable in the time-series regressions, the intercepts for stocks show the size effect of Banz (1981). The intercepts for the smallest-size portfolios exceed those for the biggest by 0.22% to 0.37% per month. These results follow the evidence in Fama and French (1992a) that, used alone, market betas leave the cross-sectional variation in average stock returns that is related to size. As in Fama and French (1992a), the simple relation between average return and beta for the stock portfolios is flat. In the Sharpe (1964)-Lintner (1965) model (beta manages to describe the cross-section of average returns and the simple relation between beta and average return is positive) but fares no better in their current test than in their earlier paper. Regarding size and BTM (value) - the two-factor time-series regressions of excess stock returns on size and BTM produce similar intercepts for those stock portfolios. The two-factor regression intercepts are, however, large (around 0.5% per month) and close to or more than two standard errors from 0. Intercepts that are similar in size support the conclusion from the cross-section regressions in Fama and French (1992a) that size and BTM factors explain the strong differences in average returns across stocks. Market, size and BTM – when the excess market return (Market) is added to the time series regressions, it pushes the strong positive intercepts for stocks observed in the two-factor (size and BTM) regressions to values close to 0. Intercepts close to 0 indicate that the regressions that use Market, size and BTM, to absorb common time-series variation in returns, do a good job explaining the cross-section of average stock returns.

Portfolios formed on E/P and DY ratios, then produced as one-factor (Market) and three-factor (Market, size, and BTM) regressions, produce compelling results. The average returns on the E/P portfolios have the U-shape documented in Fama and French (1992a), that is, the portfolio of firms with negative earnings and the portfolio of firms in the highest-E/P quintile have the highest average returns and for the positive-E/P portfolios, average return increases from the lowest- to the highest-E/P quintile. This pattern is an interesting challenge for their risk factors. The study's results confirm the evidence in Basu (1983) that the one-factor Sharpe-Lintner model leaves the relation between average return and E/P largely unexplained. For the positive-E/P portfolios, the intercepts in the one factor regressions increase monotonically, from - 0.20% per month for the lowest-E/P quintile to 0.46% for the highest. The failure of the one-factor model has a simple explanation as the market betas for the positive-E/P portfolios are all close to 1.0, so the one-factor model cannot explain the positive relation between E/P and average return. In contrast, the three-factor model that uses Market, size and BTM to explain returns leaves no residual E/P effect in average returns.

Fama and French (1992b) find that low BTM is characteristic of growth stocks - stocks with persistently high earnings on book equity that result in high stock prices relative to book equity. High BTM, on the other hand, is associated with distress, that is, persistently low earnings on book equity that result in low stock prices. The loadings on BTM in the three-factor regressions indicate that low-E/P stocks have the low average returns typical of (low-BTM) growth stocks, while high-E/P stocks have the high average returns associated with distress (high-BTM). In short. E/P portfolios produce a strong spread in average returns, which are well absorbed by the three common risk factors in stock returns. The E/P portfolios back up both the inferences of Fama and French (1993). Firstly that there are common risk factors in stock returns related to size and BTM. Secondly that Market, size and BTM capture the cross-section of average stock returns.

Portfolios formed on DY show that as in Keim (1983), average returns on portfolios formed on DY are also U-shaped; they drop from the zero-dividend portfolio to the lowest positive-DY portfolio and then increase across the positive-DY portfolios. The U-shaped pattern and the overall spread in average returns, are, however, much weaker for the DY portfolios than for the E/P portfolios. Also in line with Keim (1983) finding that the one-factor Sharpe-Lintner model leaves a pattern in average returns that looks like a tax penalty on dividends. The one-factor intercepts increase monotonically from the lowest to the highest-DY portfolios. This may suggest that pre-tax returns on higher-DY stocks must be higher to equalize after-tax risk-adjusted returns. However the apparent tax effect in average returns does not survive in the three-factor regressions that use Market, size, and BTM to explain returns. The three-factor intercepts for the five positive-DY portfolios are close to 0 and show no relation to DY. The three-factor regressions say that the increasing pattern in the average returns on the positive-DY portfolios is due to the increasing pattern in their loadings on the BTM factor. The lowest-(positive)-DY quintile has a strong negative BTM slope, and the highest-DY portfolio has a strong positive slope. Again. the three-factor model indicates that low-DY stocks have the low average returns typical of growth stocks, whereas high-DY stocks have the high average returns associated with relative distress. In summary, the results show that five factors do a great job explaining common variation in bond and stock returns and the cross-section of average returns.

In the initial paper on the three-factor model, Fama and French (1993), find that, although it captures the size and value patterns in post-1962 U.S. average returns better than the capital asset pricing model (CAPM), the model's explanation of average returns is far from complete. Further on Fama and French (2012) examines international stock returns, with two goals. Firstly to detail the size, value, and momentum patterns in average returns for developed markets, with the main contribution being evidence for size groups. Most prior work on international returns only focused on large stocks, the updated sample covers all size groups, and tiny stocks (microcaps) produce challenging results. Secondly to examine how well the multifactor model captures average returns for portfolios formed on size and value or size and momentum. They examine local versions of the models in which the explanatory returns (factors) and the returns to be explained are from the same region.

For perspective on whether asset pricing is integrated across regions, Fama and French (2012) examine models that use global factors to explain global and regional returns. The literature on integrated international asset pricing is ably reviewed by Karolyi and Stulz (2003). The papers closest to Fama and French (2012) are Griffin (2002) and Hou, Karolyi, and Kho (2011). They add to their work for example Griffin (2002) examines whether country-specific or aggregate versions of the Fama and French (1993) three-factor model better explain returns on portfolios and individual stocks in four countries, the U.S., the U.K., Canada, and Japan, where Fama and French (2012) broadens the focus onto 23 countries. Hou, Karolyi, and Kho (2011) do not examine how value premiums and momentum returns differ across size groups and whether the size patterns in average value premiums and momentum returns are captured by local and international asset pricing models— which are main tasks of their research.

There is no size premium in any region during their sample period - average size returns are all close to zero. In contrast, there are value premiums in all regions. Average returns range from 0.33% per month for North America to 0.62% for Asia Pacific. As in the U.S. results of Fama and French (1993), Kothari, Shanken, and Sloan (1995), and Loughran (1997), value premiums are larger for small stocks. The only exception being Japan, where the value premium is similar for small and large stocks. The average global BTM return is 0.45% per month, but the premium for small stocks, 0.66%, is larger than the premium for big stocks, 0.24%, and the difference, 0.42%, is 2.76 standard errors from zero. The current sample suggests that larger value premiums for small stocks are typical. The research finds value premiums in average returns in all four regions they examine (North America, Europe, Japan, and Asia Pacific). The new evidence centres on how international value varies with firm size. Except for Japan, value premiums are larger for small stocks. They test whether the value and momentum patterns in average returns are captured by empirical asset pricing models and whether such models suggest that asset pricing is integrated across regions. For evidence on market integration, the paper examines how well global explanatory returns capture average returns for global portfolios and for portfolios of the four regions. In the tests of the global CAPM, three-factor, and four- factor models on global size-value and size-momentum portfolio returns, the test rejects the hypothesis that the true intercepts are zero, but microcaps aside, the intercepts for the global four-factor model suggest that it is passable for average returns on global size-value and size-momentum portfolios.

O'Brein, Brailsford and Gaunt (2010) in an Australian study seek to disentangle the effects of Size, BTM and Momentum on returns. The researchers note that while there is reasonably clear evidence of a small firm premium in the Australian market, there is less evidence and less agreement amongst that evidence concerning the existence of the value and momentum premiums. The paper has two aims – firstly, to document the relationship between returns and the three characteristics using a new accounting data set that is far more comprehensive over time (1981-2005). Secondly, the paper examines the relationship between the characteristics (Size, BTM and Momentum), using an approach that controls for the interaction in order to measure the independent role of each characteristic in explaining returns.

One of the immediate observations from the study is that value portfolios outperform growth portfolios but more so for the small portfolios. This means the Value effect tends to be more pronounced at the small end of the market. The results demonstrate variations in returns related to Size, BTM ratios and Momentum. Specifically, the well-known Size effect is confirmed as well as the Value effect. That is, portfolios formed with stocks that possess high BTM ratios have higher returns than portfolios with low BTM ratios. Finally, it is documented that portfolios of past winners outperform past losers.

The main contribution of the O'Brein, Brailsford and Gaunt (2010) study involves the analysis of the interaction between the three characteristics with their initial evidence pointing to three key findings. First, the Size premium is the strongest (by a significant amount) in the loser portfolios. Second, the Value premium is limited to the smallest portfolios. Third, the Momentum premium is evident in the large and middle-sized portfolios, but loser stocks significantly outperform winner stocks in the smallest Size portfolio. To control for these interactions, the study uses a multivariate framework to test whether each of the characteristics influence excess returns once market risk is taken into account. The multivariate tests reveal: Firstly that market capitalization is significantly negatively related to returns. Secondly, the BTM effect is significantly positively related to returns. Thirdly, Momentum is significantly positively related to returns. In a practical sense, these findings point to where the apparent return anomalies can be found in the market.

Fama and French (2012) conclude they would be comfortable using the global four-factor model in applications to explain the returns on global portfolios – for example, to evaluate the performance of a fund that holds a global portfolio of stocks – with the condition that the portfolio does not have a strong tilt toward microcaps or toward the stocks of a particular region. This is the good news about global models and integrated asset pricing. Unfortunately, rejections on the Gibbons, Ross, and Shanken (1989) (GRS) test and large average absolute intercepts suggest that the global models do not do well when asked to explain average returns on regional size-BTM or size-momentum portfolios. This suggests shortcomings of integrated pricing across the four regions—or other bad model problems. It would not be useful to use the global models in applications to explain regional portfolio returns. This failure of the three global models in tests to explain regional returns motivates the researchers to examine local models. There is a common bottom line which is when any local model is acceptable for the size-BTM or size-momentum portfolios of a region, the local four-factor model performs as well or better than the three-factor model or the CAPM. The assets covered by this conclusion include the size-BTM portfolios of Japan, Europe, North America (without NA microcaps), and perhaps Asia Pacific, and the size-momentum portfolios of Japan and North America (again without NA microcaps). The local four-factor asset pricing models are rather successful in capturing average returns on local size-BTM portfolios, but are less successful when applied to local size-momentum portfolios.

Landsman, Maydew, Thornock (2012) examine the quality of earnings information associated with adoption of International Financial Reporting Standards (IFRS) after the predecessor set of standards, International Accounting Standards (IAS). The point of the study is to examine whether the information content of earnings announcements increases in countries following mandatory IFRS adoption and ultimately whether the information content of earnings announcements increases in countries that mandate adoption of IFRS relative to countries that retain domestic accounting standards. As South Africa has adopted IFRS, this international study will provide a conclusion that will be beneficial to this JSE study on the information content of earnings accounted for on an IFRS basis.

Their method concentrates on two measures of the information content of earnings, abnormal return volatility and abnormal trading volume in the three-day period surrounding earnings announcements. The study compares the information content of earnings announcements for firms from 16 countries before and after their countries mandated adoption of IFRS to changes in information content experienced by firms from 11 countries that retained domestic accounting standards.

Findings from the study's comparisons indicate that firms from IFRS adopting countries experienced a greater increase in abnormal return volatility and abnormal trading volume than firms from non-IFRS adopting countries. In particular, findings from country-level and firm-level estimations also indicate that firms in IFRS adopting countries experienced a greater increase in abnormal return volatility and abnormal trading volume than firms from non-IFRS adopting countries. In summary the adoption of IFRS induced investors to trade the shares that were listed in an IFRS environment as they believed the earnings had more information content about the future than shares trading in an environment that employed domestic accounting standards. This finding supports this JSE study from an IFRS perspective as local investors, like the international investors in the Landsman, Maydew, Thornock (2012) study, will likely believe there is more information content in reported earnings due to the adoption of IFRS in South Africa.

In conclusion research produced in the 1970s came together to contribute to what is known as the value effect. In the 1990s there was again valuable contributions made by Fama and French. Overall the progression of research was steady and did not face the same head winds experienced by the size effect in the 2000s. In fact from 2000 onwards there was evidence documented of integrated asset pricing and a value effect across countries. After the solid track record of the value effect it would be useful to consider its inclusion as one of the four style factors used in this paper.

Dividend yield effect

Table 2-3: Summary of dividend empirical studies reviewed

Authors	Year	Classification
Graham and Dodd	1951	Investors prefer dividends to capital gain
Lintner	1956	Dividends increase if management believes earnings change is permanent
Miller and Modigliani	1959	Dividend information content depend on managements future earnings expectations
Miller and Modigliani	1961	Dividend reductions convey information future earnings prospects poor
Lintner, Fama and Babiak	1968	Past, current earnings have dividend information content
Watts	1973	Minimal dividend information content for randomly selected firms
Black and Scholes	1974	Dividend policy affects corporation's share price
Ball	1978	Dividend effect documented
Miller	1987	Dividends lag earnings, do not lead earnings
Healy and Palepu	1988	Dividend changes indicate earnings change permanent
DeAngelo and DeAngelo	1990	Firms facing financial distress cut dividends more often than completely omitting
Leftwich and Zmijewski	1991	Dividend information content exists when companies present bad news on dividends
DeAngelo and DeAngelo	1992	Net income key determinant for dividend changes
Rao, Aggarwal and Hiraki	1992	Dividend effect in Japan
Benartzi, Michaely and Thaler	1997	Dividend changes indicate earnings change permanent
Fama and French	2001	Dividend changes due to lower propensity to pay
Huberman	2001	Investors tend to hold stocks of local companies
Visscher and Filbeck	2003	High dividend yield stock outperform
Ivkovic and Weisbenner	2005	Investors tend to hold stocks of local companies
Deshmukh	2005	Asymmetric dividend information
Becker, Ivkovic and Weisbenner	2011	Investor demand shapes firm dividend policy

Graham and Dodd (1951) produced evidence that investors prefer a dollar of dividends to a dollar of capital gain. ‘A bird in the hand is worth more than one in the bush’ approach and investors will bid up the price of companies that pay a higher dividend on average than the majority of its peers. Lintner's (1956) pioneering study of dividend policy finds that a firm's bottom line net income is the key determinant of dividend changes, which in his sample are largely dividend increases since he primarily surveys healthy firms. Essentially companies only increase dividends when management believes that earnings have permanently increased, meaning that a dividend increase implies a shift in management's perceived distribution of earnings. If one can extrapolate this finding to dividend decreases, it implies that low bottom line earnings drive dividend reductions. Lintner and Fama and Babiak (1968) emphasize the relevance of current and past earnings, while Miller and Modigliani's (1961) and Modighani and Miller's (1959) analysis of the information content of dividends suggests that dividend changes also depend on management's expectations of future earnings. Miller and Modigliani (1961) conclude that if a company does not allow its dividend policy to influence its investment decisions, and a zero tax assumption is imposed, the company’s dividend policy should not affect the price of the shares. However they explicitly suggest that dividends can convey information about future cash flows when markets are incomplete. Dividend reductions became an important field of study as a possible predictor of future earnings with Miller and Modigliani (1961) and Modigliani and Miller (1959) hypothesis that dividend reductions convey information that future earnings prospects are poor.

Black and Scholes (1974) conducted tests to determine whether or not the dividend policy of a corporation affects the price of its shares. The outcome was a tax-exempt investor might not gain by investing in high dividend yield stocks over low dividend yield stocks, other things being equal. Possible reasons are that dividend yield does not have a consistent impact of expected return for a given level of risk as increasing the average yield of a portfolio will cause it to have higher returns in some periods but then lower returns in others. In addition attempts to maximise or minimise a dividend yield in a portfolio may lead to a poorly diversified portfolio hence the expected return on the portfolio may be lower than it would have been with a better diversified portfolio. The same result applies for an investor in a high tax bracket with the assumptions of zero capital gains tax and 50% tax on dividends. This allows the investor to ignore yield in maximising the expected return of a portfolio for a given level of risk. Again if the investor pursues a low yield portfolio due to high dividend tax it will result in an unbalanced portfolio with poor diversification. The conclusion is that an investor in any tax bracket should not take dividend yield into consideration when constructing a portfolio and ultimately an investor may ignore dividends and concentrate on portfolio diversification. Further implications of these findings also apply to the corporation, as dividend policy has no lasting effect on the share price. The effect will only be temporary as a potential dividend policy change may signal to the market a change in probable future course of earnings. However once it becomes clear that the change was not made because of a future change in earnings, the effect will reduce and eventually disappear.

DeAngelo and DeAngelo (1990) conducted an empirical study into the dividend policy adjustments of 80 NYSE firms to protracted financial distress as evidenced by multiple losses during 1980-1985. The research found that all sample firms reduced dividends, and more than half apparently faced binding debt covenants in years they did so. If one removes the companies that face binding debt covenants, dividends are cut more often than omitted, suggesting that managerial reluctance is to the omission and not simply the reduction of dividends. Reinforcing this point, managers of firms with long dividend histories appear particularly reluctant to omit dividends. Finally, some dividend reductions seem strategically motivated, an example being the effort to enhance the firm's bargaining position with organized labour.

In a later study by the same authors on dividends and losses, DeAngelo and DeAngelo (1992), determine that an annual loss is essentially a necessary condition for dividend reductions in firms with established earnings and dividend records: 50.9% of 167 NYSE firms with losses during 1980-1985 reduced dividends, versus 1.0% of 440 firms without losses. In the previous study by DeAngelo and DeAngelo (1990), they document a high incidence of dividend reductions by firms with persistent (three or more) losses, but provide no evidence on dividend reductions for firms with transitory losses, or with low but positive earnings. The literature was also unclear about the relative importance of past, current, and future earnings in determining dividend changes. The DeAngelo and DeAngelo (1992) paper analyses the relation between dividend reductions and poor earnings performance by companies listed on the NYSE with established track records of positive earnings and dividend payments. They decide to focus on companies with established track records since, as Miller and Modigliani (1961) point out, dividend changes for such companies are more reliably viewed as deliberate policy shifts undertaken by management (rather than continuation of a previously established policy to preserve stable dividends). For companies with established earnings records, they are able to readily isolate a material shift in profitability, e.g., a loss following a long string of positive earnings realizations. These attributes make their sample a particularly good one with which to assess the importance of poor earnings in determining dividend reductions and to test whether dividend reductions convey incremental information about future earnings (over and above that conveyed by current earnings). They find that an annual loss is essentially a necessary, but not sufficient, condition for dividend reductions in companies with established earnings and dividend records. Approximately half (50.9%) of the loss companies reduced dividends in the initial loss year. The 50.9% dividend reduction rate for loss companies far exceeds the 1.0% incidence of dividend reductions for the portion of non-loss firms during 1980-1985. The relation between losses and dividend omissions was also dramatic: 15.0% of the loss companies omitted dividends during their initial loss year, whereas only one of the non-loss firms did so during the six-year sample period. Hence negative net income is clearly not sufficient for a dividend reduction, since almost half the companies in their loss sample did not reduce dividends during their initial loss year.

The apparent explanation DeAngelo and DeAngelo (1992) is that the loss sample is comprised of two types of companies: companies with continuing, severe earnings difficulties that reduce dividends, and companies with one-time earnings problems that do not reduce dividends. Companies that reduce dividends during the initial loss year have significantly deeper current losses on average than companies that do not reduce dividends. Dividend reducers also typically experience greater future earnings problems than do non-reducers. As hypothesized by Modigliani and Miller (1958), the analysis of the components of bottom line earnings materially improves their ability to explain which firms reduce dividends. Dividend reductions occur less often when losses include unusual income items such as special write-downs associated with corporate restructurings. Such losses are less likely to generate dividend reductions because unusual items will tend to have a transitory earnings impact and will be less indicative of ongoing operating difficulties. Thus, while Lintner (1956) is likely still correct that bottom line net income is the key determinant of dividend changes for generally healthy companies, the evidence indicates that dividend reductions are significantly better explained by net income augmented by consideration of unusual income items.

The findings also support Modigliani and Miller's (1958) and Miller and Modigliani's (1961) hypothesis that dividend reductions convey information that future earnings prospects are poor. For the sample, knowledge that a company has reduced dividends significantly improves the ability of current earnings to predict future earnings. This finding holds whether current earnings are measured as bottom line net income, net income augmented by information about unusual items, operating earnings, or operating cash flow. The researchers conjecture that this finding reflects the fact that dividends and current earnings are broad substitutes to forecasting earnings, so that dividends have information content primarily when firms have extreme or otherwise unusual earnings realizations that inherently have limited predictive power. This argument may help explain why Watts (1973) found little evidence of information content for dividend changes of randomly selected firms, while evidence of Leftwich and Zmijewski (1991) indicated that dividends have information content, but only when company announcements reveal good news about earnings and bad news about dividends.

Rao, Aggarwal and Hiraki (1992) discovered that the TSE is also characterised by a significant dividend yield effect. The effect is only prevalent in the months of January, March, June and December and the remaining months are not found to be significant. The effect is strongest in January and thus similar to that found in the U.S. One of the popular dividend yield strategies is the 'Dow-10 Investment Strategy'[3] which involves purchasing the 10 highest dividend yield stocks on the Dow Jones Industrial Average (DJIA) at 31 December and then rebalancing the portfolio every year around 31 December. Over a 50 year period the strategy outperformed the DJIA by 3.06% percentage points. This strategy was then exported to the Canadian stock exchange by Visscher and Filbeck (2003) and after taking taxes and transaction costs into account the strategy produced higher risk-adjusted returns than the Toronto 35. Similarly the strategy for the same period from 1987 to 1997 also performed well against the broader Toronto Stock Exchange 300 Index.

The idea that changes in dividends have information content remains the perceived wisdom in corporate finance. It is important to review the empirical support for the view that dividends provide information about future cash flows. Benartzi, Michaely and Thaler (1997) express that there is evidence to suggest that the market treats changes in dividends as newsworthy. When dividends are increased or initiated, prices tend to go up, and when dividends are (less often) cut or omitted, prices fall. However much less is known, about the actual realization of future earnings - whether earnings indeed do increase, as the market seems to expect. Despite the crucial role this implication has for dividend policy theories, the paper concludes that the evidence is far from conclusive. The researchers investigate whether changes in dividends have information content about the future earnings of the company. In summary, there is not much evidence to support the claim that dividend changes inform us about future earnings changes. In a study by Miller (1987) he summarizes the empirical findings as: ". . . dividends are better described as lagging earnings than as leading earnings." What they find is that there is a very strong lagged and contemporaneous correlation between dividend changes and earnings (when dividends are increased, earnings have gone up), but they are unable to find much evidence of a positive relationship between dividend

[3] This strategy was first examined by McQueen, Shields and Thorley (1997)

changes and future earnings changes. In the two years following dividend increases, they find that earnings changes are essentially unrelated to the sign and magnitude of the dividend change. However for dividend decreases, the results are stronger but perverse. Similar to Healy and Palepu (1988) results for dividend omissions, they find a clear pattern of earnings increases in the two years following dividend cuts. There is a possibility that dividend changes signal something other than the expected value of future earnings growth. Rather than a signal about future earnings growth, one possibility is that dividend increases are a signal about a permanent shift in earnings (as Lintner (1956) suggests). To answer this question, the paper compares two sets of firms that experienced similar earnings changes in a given year: the first group of firms also changed their dividends and the second did not. They find some support for Lintner's view that a dividend increase results in a permanent shift in earnings. Then changes in dividends do tell us something: earnings are unlikely to fall.

The Benartzi, Michaely and Thaler (1997) study undertook to discover whether the information content of a dividend announcement has something to do with future earnings. Consistent with the early findings of Watts (1973), they are unable to find any evidence to support the view that changes in dividends have information content about future earnings changes. While there is a strong past and concurrent link between earnings and dividend changes, the predictive value of changes in dividends is minimal. The only strong predictive power found is that dividend cuts reliably signal an increase in future earnings. They also find some evidence that dividend-increasing firms are less likely to have subsequent earnings decreases than firms that do not change their dividend despite similar earnings growth. Ultimately, changes in dividends do signal something about the present: the current increase in earnings is permanent. The conclusion we draw from this analysis is that Lintner's model of dividends remains the best description of the dividend setting process available, that is, changes in dividends mostly tell us something about what has happened. If earnings have gone up quickly in year -1 and 0, then dividends are adjusted to reflect that. The possible information content in this announcement is that the concurrent change in earnings is permanent rather than transitory.

The Fama and French (2001) study overlaps Benartzi, Michaely and Thaler (1997) by concentrating on the reasons behind a company’s decision to reduce or omit dividends. They seek to determine whether the decision is driven by changing company characteristics or a lower propensity to pay. They study the incidence of dividend payers during the 1926-99 period, with special interest in the period after 1972, covering NYSE, AMEX, and NASDAQ companies.

The percent of companies paying dividends declines sharply after 1978. In 1973, 52.8% of publicly traded non-financial non-utility firms pay dividends. The proportion of payers rises to a peak of 66.5% in 1978. It then falls sharply. In 1999, only 20.8% of firms paid dividends. The decline after 1978 in the percent of companies paying dividends raises three questions. Firstly what are the characteristics of dividend payers? Secondly is the decline in the percent of payers due to a decline in the prevalence of these characteristics among publicly traded companies, or thirdly have companies with the characteristics typical of dividend payers become less likely to pay? They address these questions.

The decline after 1978 in the percent of firms paying dividends is due in part to an increasing tilt of publicly traded companies toward the characteristics of companies that have never paid - low earnings, strong investments, and small size. This tilt in the population of firms is driven by an explosion of new listings, and by the changing nature of the new companies. It is perhaps that investors have become more willing to hold the shares of small, relatively unprofitable growth companies. But the resulting tilt of the publicly traded population toward such companies is only half of the story for the declining incidence of dividend payers. The more striking finding is that companies have become less likely to pay dividends, whatever their characteristics. They characterize the decline in the likelihood that a company pays dividends, given its characteristics, as a lower propensity to pay. The perceived benefits of dividends (whatever they are) have declined through time. Due to the declining incidence of dividend payers two questions are raised: (a) Has the population of companies drifted toward a lower frequency of companies with the characteristics typical of payers, or (b) have companies with the characteristics typical of payers become less likely to pay dividends? They start by establishing the characteristics of dividend payers, and the declining incidence of these characteristics among publicly traded companies.

The population of dividend payers shrank by more than 50% after 1978. It is documented that the characteristics of dividend payers and the progressive tilt of the population of publicly traded companies toward the characteristics of firms that have never paid. The characteristics of dividend payers focuses on the summary statistics that payers and non-payers differ in terms of profitability, investment opportunities, and size. The results on the characteristics of dividend payers and non-payers complement the evidence in Fama and French (1999) that among dividend payers, larger and more profitable companies have higher payout ratios, and firms with more investments have lower payouts. All these results are also consistent with the Myers and Majluf (1984) pecking-order model in which companies are reluctant to issue risky securities because of asymmetric information problems or simply because of high transactions costs. Bigger asymmetric information problems and higher costs when issuing securities can also explain why smaller companies are less likely to pay dividends. More profitable firms pay more dividends while firms with more investments pay less is also consistent with the propositions of Easterbrook (1984) and Jensen (1986) about the role of dividends in controlling the agency costs of free cash flow.

In terms of profitability dividend payers have higher measured profitability than non-payers for the full 1963-98 period. Like profitability, investment opportunities differ across dividend groups. Companies that have never paid dividends have the best growth opportunities and evidence indicates much higher asset growth rates for 1963-98 (16.50% per year) than dividend payers (8.78%) or former payers (4.67%). Regarding size, dividend payers are much larger than non-payers. During 1963-67, the assets of payers average about eight times those of non-payers.

Dividend payers are more profitable and non-payers derive more of their market value from expected growth, so the share of dividend payers in aggregate earnings is even higher than their share of assets and market values. During each of the four five-year periods from 1973 to 1992, payers account for about 97% of common stock earnings. However for 1993-98, 23.6% of firms that pay dividends account for all but 8.3% of aggregate earnings. The evidence suggests that three fundamentals of profitability, investment opportunities, and size are factors in the decision to pay dividends. Dividend payers tend to be large, profitable companies with earnings on the order of investment outlays. Companies that have never paid are smaller and they seem to be less profitable than dividend payers, but they have more investment opportunities (higher asset growth rates) and their investment outlays are much larger than their earnings. The salient characteristics of former dividend payers are low earnings and few investments.

Qualitative evidence is presented on the reduced propensity to pay dividends. The surge in new listings in the 1980s and 1990s, and the changing nature of new lists, cause the population of publicly traded companies to tilt increasingly toward the characteristics - small size, low profitability, and strong growth opportunities - of companies that have never paid dividends. But it is believed that this is not the whole story for the decline in the percent of dividend payers. The more interesting result is that, given their characteristics, companies have become less likely to pay dividends. The research proves that the changing characteristics of firms combine with lower propensity to pay explains the decline in the incidence of dividend payers. If the decline in the percent of dividend payers is due entirely to the changing characteristics of companies, companies with particular characteristics should be as likely to pay dividends now as in the past. In 1978, 72.4% of companies with positive common stock earnings pay dividends. In 1998, 30.0% of profitable companies pay dividends, less than half the fraction for 1978. These results suggest that dividends become less likely among companies with the characteristics (positive earnings and earnings in excess of investment) of dividend payers. But unprofitable companies and companies with investment outlays that exceed earnings also become less likely to pay.

In conclusion the proportion of companies paying cash dividends falls from 66.5% in 1978 to 20.8% in 1999, due in part to the changing characteristics of publicly traded companies. Fed by new listings, the population of publicly traded companies tilts increasingly toward small firms with low profitability and strong growth opportunities. These are characteristics typical of companies that have never paid dividends. More interesting, the research found that regardless of their characteristics, companies have become less likely to pay dividends. The evidence that, controlling for characteristics, companies become less likely to pay dividends says that the perceived benefits of dividends have declined through time. Some of the possibilities reasons are: (1) lower transactions costs for selling stocks for consumption purposes, in part due to an increased tendency to hold stocks via open end mutual funds; (2) larger holdings of stock options by managers who prefer capital gains to dividends; and (3) better corporate governance technologies (example more prevalent use of stock options) that lower the benefits of dividends in controlling agency problems between stockholders and managers. This lower propensity to pay is at least as important as changing characteristics in the declining incidence of dividend-paying firms. This relatively steady termination rate of dividends is consistent with the evidence in DeAngelo and DeAngelo (1990) and DeAngelo et al. (1992) that only distressed firms (with strongly negative earnings) terminate dividends.

Arnott and Asness (2003) investigate whether dividend policy, as observed in the payout ratio of the U.S. stock market, forecasts future aggregate earnings growth. The discussion focuses on 1946-2001 (the post-World War II period) as the "modern period," for which the confidence in data quality can be the highest. The period before 1946 was one of two world wars, the Great Depression and unregulated markets with a host of differences from the post-1945 era. The research divides the period January 1946 to December 1991 into four quartiles with rolling 10-year periods by the period’s starting payout ratio (quartile 1 being the low payout ratio and quartile 4 being the high)

The results show that the average earnings growth over the rolling 10 year periods increases with a rising starting payout ratio. Alternatively when reviewing the bottom quartile of payout ratios, the average subsequent real earnings growth is actually negative. The worst and best 10-year spans also show the same monotonic relationship with the starting pay-out ratio: The higher the payout ratio, the better the average subsequent 10-year earnings growth and the better the best and the worse the worst out-comes.

The possible hypotheses noted by Arnott and Asness (2003) that might explain the positive relationship between current payout ratio and future real earnings growth is firstly, corporate managers are loath to cut dividends (Lintner, 1956) and perhaps a high payout ratio indicates managerial confidence in the stability and growth of future earnings and a low payout ratio suggests the opposite. Secondly, there is a hypothesis that companies sometimes retain too much of their earnings as a result of the managers' desires to build empires (Jensen, 1986). A policy of earnings retention may end up encouraging empire building by creating an irresistible cash hoard burning a hole in the corporate pocket. Conversely, financing through share issuance and paying substantial dividends may subject management to more scrutiny, reduce conflicts of interest, and thus curtail empire building. The main assumption is that inefficient empire building lays the foundation for poor earnings growth in the future whereas discipline and a minimization of conflicts has the opposite effect. Thirdly, the positive relationship maybe driven by sticky dividends (Lintner, 1956) which is combined with mean reversion in more volatile earnings. Temporary peaks and troughs in earnings, subsequently reversed, could cause the payout ratio to be positively correlated with future earnings growth in the form of temporarily low earnings today cause a high payout ratio, thus forecasting the earnings snapback tomorrow. The testable difference between this hypothesis and the first two is that dividend policy has no special standing, so a measure of mean reversion in earnings should work to forecast future earnings growth.

Gwilym, Seaton and Thomas (2005) investigate whether high-dividend portfolios on the U.K. stock market that also possess high-payout ratios outperform both the market and other high-dividend strategies. The research finds that when risk and transaction costs are considered, most of the excess returns to high-dividend portfolios are removed and index portfolios were the best performers. However when high-payout ratio was combined with high-dividend yield it produced excess returns over the index portfolios and pure-dividend strategies.

Jiang and Lee (2007) create a combined log-linear model to forecast expecetd returns on the U.S. market. The combined model includes dividend yield and BTM. The empirical research finds that expected excess return has a positive relation with dividend yield and BTM ratio in both cross-section and time-series relations. The finding convey that it is quite possible that dividends, book value and market value are cointegrated, sharing a common trend that may reflect a permanent component of fundamentals. The authors provide a possible explanation that market value and book value tend to move together over time around their fundamental variables such as earnings and dividends. The model's superior performance also suggests that the spread may contain useful information that is not contained in either the dividend yield or the BTM ratio separately.

Deshmukh (2005) examines the effect of asymmetric information on dividend policy in light of an alternative explanation based on the pecking order theory. Previous research on why firms pay dividends focus on agency costs (Rozeff, 1982; Easterbrook, 1984), asymmetric information (Bhattacharya, 1979; Miller and Rock, 1985; and John and Williams, 1985) and transaction costs (Black and Scholes, 1974; Litzenberger and Ramaswamy, 1980; Miller and Scholes, 1982). The paper empirically examines an alternative explanation of dividend policy based on asymmetric information. This alternative explanation is based on the implications of the pecking order theory from Myers (1984) and Myers and Majluf (1984). The pecking order theory provides implications for a firm's dividend policy which have been largely ignored in the empirical literature on dividend policy. Myers and Majluf (1984) argue that in the presence of asymmetric information, the firm may from time to time underinvest. The underinvestment occurs when the firm has inadequate funds to investment does not want to bear the lemons-premium associated with new capital issues. A firm can reduce underinvestment by financing investments with slack that can be accumulated through retention (or by decreasing dividends). Their analysis implies that the need for slack increases with the level of asymmetric information between the firm and its outside investors. This reasoning suggests that the higher the level of asymmetric information, the lower the dividends.

Deshmukh's second contribution is the inclusion of both dividend-paying and non-dividend-paying firms in their empirical analysis as the majority of previous empirical studies have ignored non-dividend-paying firms. If firms find it optimal not to pay dividends, their exclusion from may create a selection bias in the sample resulting in biased and inconsistent estimates of the underlying parameters. The paper's findings indicate that the inclusion of an asymmetric information variable allows a distinction to be drawn between the two competing asymmetric information explanations of dividend policy that has not been drawn before. The results indicate that firms with less asymmetric information pay a higher dividend which is consistent with the pecking order theory but inconsistent with the signalling theory. Their results also suggest that the previous findings on the role of insider ownership in determining dividend policy appear to be more strongly related to asymmetric information (and the pecking order theory) than to agency costs.

From the empirical results it can be concluded that dividends are positively related to both analyst following and cash flow, but negatively related to growth opportunities. A higher analyst following also may imply less asymmetric information. The positive relation between dividends and analyst following is consistent with the pecking order theory. The positive relation between dividends and cash flow and the negative relation between dividends and growth opportunities are also consistent with the pecking order theory. The results also indicate that dividends are unrelated to the insider ownership variable when the level of asymmetric information is controlled. This finding suggests that the relation between insider ownership and dividend policy appears to be more strongly related to asymmetric information than to agency costs. Finally the negative relation between dividends and the amount raised through equity issues provides further support for the pecking order theory.

Becker, Ivkovic and Weisbenner (2011) examine the role of investor demand in shaping corporate payout policy and that firms may actively respond to the preferences of their current shareholders. They test whether shareholder demand for dividends influences firm payout policy. The challenge is to quantify dividend demand, that is, to find a variable that reflects investor demand for dividends, but does not also proxy for dividend supply from firms. Dividend supply can be firms that are more likely to pay or supply dividends because of a lack of investment opportunities. The paper seeks to identify the effect of dividend demand on firm policy by reviewing the geographical variation in the population of retail investors. The identification strategy is based upon two notions - first, seniors have a preference for dividend-paying stocks (Miller and Modigliani, 1961; Shefrin and Thaler, 1988) because older investors likely have more pronounced needs to “cash out” larger portions of their portfolios for consumption and also likely have lower tax rates on dividends relative to younger investors. These motivations suggest greater demand for dividends from senior investors. Second, household stock ownership tends to be local - the tendency of individual investors to hold stocks of local companies in the US has been reported by numerous studies (Huberman, 2001; Ivkovic and Weisbenner, 2005). The variation in local age structure, therefore, induces differential dividend preferences across locations and companies located in areas with more seniors will face higher demand for dividends.

This implies that it is possible to identify a component of the dividend demand facing individual firms. This demand proxy is the variable Local Seniors - defined as the fraction of residents who are 65 years old or older in the county in which a company is headquartered. Local seniors is used to test whether geographically varying dividend demand is a determinant of payout policy for U.S. corporations. The paper concludes that there is a tendency of older investors to hold dividend-paying stocks in combination with individual investors' inclination to hold local stocks results in stronger dividend demand for companies located in areas with many seniors. Demographics provide an empirical proxy for dividend demand as there is a significant positive effect of Local Seniors - the fraction of seniors in the county in which a firm is located - on the firm's propensity to pay dividends, its propensity to initiate dividends and its dividend yield. The effect of Local Seniors on the company's decision to start paying dividends is particularly strong and is of the same economic magnitude as other key determinants such as company size and age. The main implication of their findings is that corporations respond to the preferences of their owners when setting payout policy.

In conclusion the origins of the dividend effect can be traced right back to the 1950s with the findings by Graham and Dodd. There was a concerted focus from 1960 to 1990 on the information content of dividends. Research considered a firm's action towards dividend changes to possess information content about future returns. These actions took the form of dividend increases, reductions and omissions – with later being the least popular amongst management. From 2000 onwards research began to focus on the possibility that corporate culture towards dividends may have permanently shifted. Broadly during this period research argued that even cash laden firms began to shy away from dividends. During the 2000s a separate branch of research concluded that investor demand can shape management's policy towards dividends. Evidence in this section also indicates that high dividend yield stocks outperform their low dividend yield counterparts. In summary after the compelling evidence of a dividend effect, over a period stretching from the 1950s up to recent times, it was decided to select the dividend effect as a worthwhile style factor for inclusion in this paper.

Liquidity effect

Table 2-4: Summary of liquidity empirical studies reviewed

Authors	Year	Classification
Kraus and Stoll	1972	Price impact on the bid-ask spread
Amihud and Mendelson	1980	Illiquidity is due to adverse selection costs
Kyle	1985	Positive relationship between transaction volume and price change
Glosten and Milgrom	1985	Illiquidity is due to inventory costs
Keim and Madhavan	1996	Large excess demand results in large price impact
Amihud and Mendelson	1986	Positive relationship between bid-ask spread and price
Brennan and Subrahmanyam	1996	Illiquidity positively affects stock returns
Eleswarapu	1997	Positive relationship between bid-ask spread and price
Chalmers and Kadlec	1998	Amortized effective spread positively affects price
Lustig	2001	Solvency constraints give rise to liquidity risk
Holstrom and Tirole	2001	Share return related to sensitivity of aggregate liquidity
Pastor and Stambaugh	2001	Illiquidity effect stronger on small stock portfolios
Amihud	2002	Expected stock excess return reflects an illiquidity premium
Pastor and Stambough	2003	Liquidity factor included in Fama and French three factor model and has strong explanatory power
Liu	2006	Capture multiple dimensions of liquidity to emphasize order execution difficulty
Ibbotson, Chen, Kim and Hu	2013	Liquidity is given equal standing as investment style next to size, value and momentum styles

Liquidity of a listed stock is generally described as the ability to trade large quantities quickly at low cost with little price impact. Illiquidity reflects the impact of order flow on price - the discount that a seller concedes or the premium that a buyer pays when executing a market order - that results from adverse selection costs and inventory costs (Amihud and Mendelson (1980); Glosten and Milgrom, (1985)). For standard-size transactions, the price impact is the bid–ask spread, whereas larger excess demand induces a greater impact on prices (Kraus and Stoll (1972); Keim and Madhavan, (1996)), reflecting a likely action of informed traders. Kyle (1985) proposed that because market makers cannot distinguish between order flow that is generated by informed traders and by liquidity (noise) traders, they set prices that are an increasing function of the imbalance in the order flow which may indicate informed trading. This creates a positive relationship between the order flow or transaction volume and price change, commonly called the price impact.

These measures of illiquidity are employed in studies that examine the cross section effect of illiquidity on expected stock returns. Amihud and Mendelson (1986) with a study on NYSE/AMEX stocks, 1961–1980 and Eleswarapu (1997) study on NASDAQ stocks, 1974–1990 found a positive effect of quoted bid–ask spreads on stock returns. Chalmers and Kadlec (1998) as a measure of liquidity used the amortized effective spread, obtained from quotes and subsequent transactions, and found that it positively affects stock returns. The effective spread is derived from the absolute difference between the mid-point of the quoted bid–ask spread and the transaction price that follows, classified as being a buy or sell transaction. The spread is divided by the stock's holding period, which is obtained from the turnover rate on the stock, to obtain the amortized spread. Brennan and Subrahmanyam (1996) measured stock illiquidity by price impact, measured as the price response to signed order size, and by the fixed cost of trading, using intra-day continuous data on transactions and quotes. They all found that these measures of illiquidity positively affect stock returns.

The size (market value of the stock) is also related to liquidity since a larger stock issue has smaller price impact for a given order flow and a smaller bid–ask spread. Stock expected returns are negatively related to size (Banz, 1981; Reinganum, 1981; Fama and French, 1992). This is consistent with size being a proxy for liquidity in Amihud and Mendelson (1986). Barry and Brown (1984) propose that the higher return on small companies' stock is possibly due to the compensation for less information available on small companies that have been listed for a shorter period of time. This is consistent with the illiquidity explanation of the small firm effect since illiquidity costs are increasing in the asymmetry of information between traders as found by Glosten and Milgrom, (1985) as well as Kyle (1985). Amihud, Mendelson and Wood (1990) studied the October 19, 1987 stock market crash and focused on the relationship between market liquidity and market return. They concluded that the crash was associated with a rise in market illiquidity and that the price recovery by October 30 was associated with improvement in stock liquidity.

Amihud (2002) considers illiquidity and stock returns from the NYSE during the period 1964–1997. The paper shows that over time, expected market illiquidity positively affects ex ante stock excess return, suggesting that expected stock excess return partly represents an illiquidity premium. This complements the cross-sectional positive return–illiquidity relationship and it is found that stock returns are negatively related over time to unexpected illiquidity changes. Illiquidity affects more strongly small firm stocks, which explains the time series variations in their premiums over time. The hypothesis on the relationship between stock return and stock liquidity is that returns increase in illiquidity, as proposed by Amihud and Mendelson (1986). The researcher proposes that expected stock excess return also reflects compensation for expected market illiquidity, and is thus an increasing function of expected market illiquidity. The documented results are consistent with this hypothesis. Unexpected market illiquidity also lowers contemporaneous stock prices. A possible reason is due to higher realized illiquidity, raising expected illiquidity, which in turn raises stock expected returns and lowers stock prices - assuming no relation between corporate cash flows and market liquidity. This hypothesis too is supported by the results. These illiquidity effects are shown to be stronger for small firms' stocks and suggests that variations over time in the ‘‘size effect’’- the excess return on small firms' stocks - are related to changes in market liquidity over time.

The proposition tested is that expected stock excess return is an increasing function of expected market illiquidity. The tests overlap the methodology of French, Schwert and Stambaugh (1987) that tested the effect of risk on stock excess return. In an extreme case of a rise in illiquidity during the October 1987 crash there was a ‘‘flight to liquidity’’: the more liquid stocks declined less in value, after controlling for the market effect and the stocks' beta coefficients. This may suggest the existence of two effects on stock return when expected market illiquidity rises: (a) A decline in stock price and a rise in expected return, common to all stocks. (b) Substitution from less liquid to more liquid stocks (‘‘flight to liquidity’’). For low-liquidity stocks the two effects both affect stock returns in the same direction. For liquid stocks the two effects work in opposite directions. Unexpected rise in market illiquidity, which negatively affects stock prices, increases the relative demand for liquid stocks and mitigates their price decline. While higher expected market illiquidity makes investors demand higher expected return on stocks, it also makes liquid stocks relatively more attractive, thus weakening the effect of expected illiquidity on their expected return.

The results suggest that the effects of market illiquidity (both expected and unexpected) are stronger for small firm stocks than they are for larger firms. These findings could also possibly explain the variation over time in the ‘‘small firm effect’’ as documented by Brown, Kleidan and Marsh (1983) who also ‘reject the hypothesis that the ex-ante excess return attributable to size is stable over time.

The findings here explain why: small and large companies react differently to changes in market illiquidity over time. The greater sensitivity of small stock returns to market illiquidity means that they have greater illiquidity risk. Pastor and Stambaugh (2001) argue that stocks with greater illiquidity risk earn higher illiquidity risk premium if this risk is priced in the market. Amihud (2002) concurs with the Pastor and Stambaugh (2001) findings and concludes that the effects over time of illiquidity on stock excess return differ across stocks by their liquidity or size. The effects of both expected and unexpected illiquidity are stronger on the returns of small stock portfolios. This suggests that the variations over time in the ‘‘small firm effect’’ (the excess return on small firms' stock) is partially due to changes in market illiquidity. He concludes that in times of dire liquidity, there is a ‘‘flight to liquidity’’ that makes large stocks relatively more attractive. The greater sensitivity of small stocks to illiquidity means that these stocks are subject to greater illiquidity risk which, if priced, should result in higher illiquidity risk premium.

Liu (2006) researched the trading speed dimension of liquidity. Few studies incorporate a liquidity risk factor into an asset pricing model, and those that do observe limited success in explaining cross-sectional variation in asset returns. Pastor and Stambaugh (2003) lead the way here by incorporating a liquidity factor into the Fama–French three-factor model. They show that their liquidity risk factor explains half of the profits to a momentum strategy over the period 1966–1999. In the Liu (2006) study proposes a new liquidity measure for individual stocks, which is defined as the standardized turnover-adjusted number of zero daily trading volumes over the prior 12 months. This measure captures multiple dimensions of liquidity such as trading speed, trading quantity, and trading cost, with particular emphasis on trading speed - the continuity of trading and the potential delay or difficulty in executing an order. The new liquidity measure is highly correlated with the commonly used bid-ask spread, turnover, and return-to-volume measures. However, even with high correlation to traditional measurements of liquidity, the new measure is materially different from existing measures. The new liquidity measure introduced by Liu (2006) is designed in particular to emphasize order execution difficulty. The research finds that the new liquidity measure identifies stocks as less liquid tend to be small, value, low-turnover and high bid-ask spread, which are consistent with intuition. The least liquid decile of stocks significantly outperform the most liquid decile of stocks. The liquidity premium is also robust to various controls for firm characteristics known to be associated with stock returns such as size, BTM, turnover, low price, and past intermediate-horizon returns. Within NYSE stocks, the return difference between the second-least liquid decile and the most liquid decile is also significant which indicates that the liquidity premium remains significant after excluding the decile of stocks with the largest number of days without trades. These excluded stocks will likely consist of those stocks that investors are unaware of or that they simply find uninteresting. Very interestingly is that neither the CAPM nor the Fama–French three-factor model can account for the liquidity premium.

This pronounced premium associated with the new liquidity measure raises two immediate questions: Firstly, why is there a liquidity premium? Secondly what causes a stock to be less liquid? To answer these questions Lustig (2001) shed promising light on the role that liquidity risk plays in explaining asset prices and argues that solvency constraints give rise to liquidity risk. According to Lustig's model, investors demand a higher return on stocks to compensate for business cycle-related liquidity risk, that is, low stock returns in recessions. In addition, he shows that a stock's sensitivity to liquidity raises its equilibrium expected return. Focusing on the corporate demand for liquidity, Holmstrom and Tirole (2001) develop a liquidity-based asset pricing model and show that a security's expected return is related to its sensitivity to aggregate liquidity. Pastor and Stambaugh (2003) argue that any investor who employs some form of leverage and faces a solvency constraint will require higher expected returns for holding assets that are difficult to sell when aggregate liquidity is low. They document that stocks with high sensitivity to aggregate liquidity generate higher returns than low-sensitivity stocks, and conclude that market-wide liquidity is an important variable for asset pricing.

Assuming the average investor does face solvency constraints, one can consider the factors that affect a security's liquidity, even if, as Pastor and Stambaugh (2003) observe, the complete economic theory has yet to be formally modelled. First, liquidity becomes a relevant issue when the economy is in a recessionary state. From the viewpoint of asset allocation, risk-averse investors would prefer to invest in less risky, more liquid assets if they anticipate a recession. This follows the Hicks (1967) ''liquidity preference'' notion, according to which investors hold financial assets not only for their returns but also to facilitate adjustments to changes in economic conditions. This is also consistent with Chordia, Sarkar and Subrahmanyam. (2005), who show that stock market liquidity is associated with monetary policy and that fluctuations in liquidity are pervasive across stock and bond markets, as wells as with Eisfeldt (2002), who models endogenous fluctuations in liquidity along with economic fundamentals such as productivity and investment. In addition, it may be difficult for corporations to raise funds in the capital markets when the economy is performing poorly, in which case companies have an incentive to hoard liquidity as seen by Holmstrom and Tirole (2001).

Secondly, asymmetric information between market participants can create illiquidity. Insider traders who possess private information in the market and when (uninformed) investors become aware of this, then the uninformed investors will choose not to trade - restricting liquidity. During extreme scenarios, the market can even collapse. Therefore, the private information premium that Easley, Kiefer, O'Hara and Paperman (2004) document in their study can be related to or captured by the liquidity premium.

Thirdly, companies themselves can cause (il)liquidity. No investor is interested in holding the shares of a company that has a high probability of default or has a poor management team. The study postulates that liquidity risk can, to some extent, capture any default premium. Likewise, distressed firms are unattractive to investors and therefore become less liquid. The research also finds that small and high BTM stocks are less liquid. Liu (2006) therefore argues that a liquidity factor captures distress risk more directly than the size and BTM proxies used in the Fama–French three factor model. The evidence that liquidity is an important state variable for asset pricing as found by Pastor and Stambaugh (2003) and the limited power of the Fama–French three-factor model to describe the cross-section of asset returns as documented by Daniel and Titman (1997) motivates the researcher to develop a liquidity-augmented asset pricing model.

Specifically, the paper develops a two-factor augmented CAPM that comprises both market and liquidity factors. It is found that the mimicking liquidity factor is highly negatively correlated with the market, reflecting its nature as a state variable - when the economy performs badly, causing liquidity to be low, investors require a high liquidity premium to compensate them for bearing high liquidity risk. Pastor and Stambaugh (2003) suggest a direction for future research into the role that liquidity risk plays in explaining the various pricing anomalies. The two-factor model that Liu (2006) developed successfully explains the documented anomalies such as the liquidity premium that both the CAPM and the Fama–French three-factor model fail to capture and subsumes the effects due to size, BTM, cash-flow-to-price, E/P and DY. The CAPM performs poorly against these market anomalies and the Fama–French three-factor model has only limited power in explaining some of these anomalies.

Ibbotson, Chen, Kim and Hu (2013) argue that liquidity should be given equal standing with size, value/growth and momentum as an investment style. Sharpe (1992) defined four criteria that characterize a benchmark style: (1) "identifiable before the fact," (2) "not easily beaten," (3) "a viable alternative," and (4) "low in cost." Ibbotson et al examined stock-level liquidity in the top

3,500 market-capitalization universe of U.S. equities over 1971–2011 and subjected it to the four style tests of Sharpe (1992). They use stock turnover, which is a well-established measure of liquidity that is negatively correlated with long-term returns in the U.S. equity market [see Haugen and Baker (1996); Datar, Naik, and Radcliffe (1998)]. Their empirical findings, which amplify the existing literature, are that liquidity meets all four criteria as an investment style. To compare liquidity to other well-known style factors value versus growth is measured by PE ratios (Basu 1977), BTM (Fama and French 1992, 1993) and DY ratios are also used.

The returns of the low-liquidity quartile were comparable to those of the other styles, beating size and momentum but trailing value. All four styles were considered "not easily beaten." Double-sorted portfolios were also examined, comparing liquidity with size, value, and momentum in four-by-four matrices. The impact of liquidity on returns was stronger than that of size and momentum and roughly comparable to that of value. It was also additive to each style when the portfolios were double sorted. It was thus determined that liquidity is "a viable alternative" to size, value, and momentum. Using the simple stock-level characteristic of stock turnover, it was shown that liquidity is "identifiable before the fact." Also through both single- and double-style portfolio returns, it was shown that liquidity is "not easily beaten." The regression and covariance results show that liquidity is "a viable alternative." By using a low-portfolio-turnover strategy the results also show that liquidity may be managed "low in cost". In conclusion, Ibbotson et al (2013) demonstrated that liquidity meets all four of Sharpe's criteria for a benchmark style.

In summary the liquidity of stocks has been of keen interest to researchers as it can be measured accurately in the form of readily available data such as bid-ask spreads and stock turnover. The liquidity effect on a share's price can be explained by numerous theories covered in this section such as adverse selection costs, inventory costs, solvency restraints and asymmetric information. Ibbotson et al (2013) conclude that liquidity must be given equal standing as an investment style next to size, value and momentum strategies. Hence the liquidity will be selected as one of the style factors of this paper.

2.3.3 South African research

Table 2-5: Summary of South African empirical studies reviewed

Authors	Year	Classification
De Villiers, Lowlings, Pettit and Affleck-Groves	1986	Documented return anomalies on the JSE
Plaistow and Knight	1986	Early finding of the value effect
Page and Palmer	1993	No evidence of a size effect but noted an earnings effect
Page	1996	Early contradiction of the CAPM on the JSE
Van Rensburg	2001	Value, quality and momentum factors explain returns
Van Rensburg and Robertson	2003a	Identity given to style based factors that explain cross section of JSE returns
Van Rensburg and Robertson	2003b	No relationship between market beta and average return. Size and PE better explain returns
Auret and Sinclaire	2006	Size and PE are best indicators for a two factor model but BTM is useful on its own
Mutooni and Muller	2007	Value outperforms a growth strategy when using a style timing strategy
Basiewicz and Auret	2009	Restrict portfolio formation by price and liquidity and note size and value effects reduced
Janse van Rensburg, Friskin and Sharp	2009	Smaller firm portfolios observe higher volatility than large firm portfolios when market volatility increases
Strugnell, Gilbert and Kruger	2011	Over an updated sample period conclude that size and value effect apparent on the JSE
Hoffman	2012	Concludes size, value and momentum effects present on the JSE

De Villiers, Lowlings, Pettit and Affleck-Graves (1986) are amongst the first to uncover isolated ‘anomalies’ on the JSE within the framework of traditional asset pricing theory. They investigated the small firm effect and found no evidence of it on the Johannesburg Securities Exchange (JSE).

They did however find evidence for a large firm effect, which they attributed to the predominance of institutional investors and extensive cross holdings found in listed companies on the JSE. Similarly, Page and Palmer (1991) also found no evidence of a small firm effect on the JSE but documented evidence of an earnings effect on the JSE. However, the research methodologies were not designed to determine the identity of these anomalies and hence no evidence of a small size effect was documented.

In a similar study by Page (1996) the performance of the CAPM is compared to a three and five factor version of the APT in explaining the earnings-to-price and size anomalies. The study produced evidence of an earnings-to-price effect but again no significant small size effect was observed. A potential explanation for the lack of a size effect in earlier South African studies, in addition to design shortcomings of research methodologies, is possibly due to the small sample sizes used in the studies and liquidity. After the introduction of the Johannesburg Equity Trading (JET) system in 1996 there have been significant improvements in liquidity.

Van Rensburg (2001) was the beginning of a movement of research that successfully documented style factors. The paper adopts the ‘portfolio-based’ approach to search for the presence of style-based effects. The outperformance of small capitalisation stocks is noted after risk adjustment using both the CAPM and a two factor APT model. This is one of the first major steps in South African research uncovering the small firm effect. The paper used monthly return data of industrial shares on the JSE between the period 1983 and 1999 and examined more than 20 style strategies using a portfolio approach. It was found that 11 of these 20 portfolios were found statistically significant. Using cluster analysis the research concluded that three style grouping emerged. Namely the ‘value’ cluster made up of earnings yield, dividend yield, price to NAV and prior five-year’s earnings growth. Then the ‘quality’ cluster consisting of size, turnover, leverage and cash flow-to-debt and lastly the ‘momentum’ cluster comprising the last three, six and twelve month’s returns.

Van Rensburg and Robertson (2003a) moves from the ‘portfolio-based’ approach to the ‘characteristic-based’ approach but continue the same strand of research as Van Rensburg (2001). JSE share returns from the period 1990 to 2000 are regressed on the values of various style characteristics as observed at the beginning of the period. The estimated slope-coefficients from the time series represent the rewards accruing to each characteristic in each period while the share’s exposure to the factor is directly observable by the value of the characteristic concerned. The central concern of their study was to discern the identity of the style-based factors that explain the cross-section of the JSE returns. The 24 individual share-level characteristic attributes are regressed against their share returns and from this procedure a short-list of six candidate factors are filtered as being the most significant to explain share returns. These six emerging factors were price-to-NAV, DY, PE, cash flow-to-price, price-to-profit and size. Using these six factors a multifactor model is run to decide which combination of factors are the most significant in explaining share returns. A two-factor characteristic-based model emerges using size and PE as the best explanatory variables for the cross-section of JSE returns. The explicit aim of this study was to produce a style based model of expected returns for the JSE but it can also be seen as uncovering the anomalies present in the JSE, which disputes the CAPM. Even a two factor APT model does not remove the anomalies identified.

Van Rensburg and Robertson (2003b) from the basis of their findings of size and PE from Van Rensburg and Robertson (2003a), again select these variables for more detailed examination. In particular the relationship between these effects and the explanatory power of beta is investigated. Fama and French (1992) evaluate the role of beta in the presence of CAPM anomalies associated with size, leverage, BTM and EY attributes. They conclude when there is a variation in market beta that is unrelated to size, there is no longer a relationship between market beta and average return – hence the positive relationship between beta and returns is the size effect in disguise. The results lead Fama and French (1992) to a two factor style-based model of expected returns that are not consistent with the CAPM. In the Van Rensburg and Robertson (2003b) paper the findings show that the size attribute on the JSE is significantly positively correlated to pre-ranking beta – this could be due to a 'double counting' effect due to the concentration of large stocks in the capitalization-weighted market indices. To illustrate this point the top five JSE shares comprised 50% of the market capitalization of the JSE in January 2002. Whether the negative relationship between size and beta persists after adjustments to the top heavy nature of the JSE is a topic of research outside the scope of their paper. The authors note that if these adjustments were made they would have to be extraordinarily powerful to reverse the negative relationship observed in their study and most of the findings of their study would not be affected by any adjustments of this nature. Over the study period the PE attribute proves to be not significantly correlated with beta. Also low PE stocks (value) outperform their highly rated counterparts. In summary the size sorted portfolios bode worse for beta on the JSE compared with international evidence. The reason is that the study shows that small size earns a higher return on the JSE but also has a lower beta. It is further documented that portfolios containing Low-PE stocks earn higher average returns and also have lower betas. When taking this result in combination with pre-ranking betas their study finds for the first time on the JSE that beta may even be inversely related to returns.

An interesting extension of Van Rensburg and Robertson (2003a) was the work conducted by Auret and Sinclaire (2006). They found book-to-market equity ratio to be a better indicator of the value premium than PE ratio, contrary to the findings of Van Rensburg and Robertson (2003b). They argue that book-to-market completely subsumed not only PE ratio, but also firm size, in multiple regressions on return. However, when book-to-market was included in a multifactor model it did not result in greater explanatory power than a two-factor model using PE ratio and size. They attributed this finding to the high correlation between book-to-market and other candidate variables, while PE ratio and size have the virtue for modelling purposes of low correlation and hence a reduced multi-collinearity problem. This suggests that one may reasonably use market capitalization and PE ratio as the size and value indicators respectively in a two factor model due to their low multi-collinearity, but book-to-market would however be a useful extension on its own.

Mutooni and Muller (2007) investigate style-timing strategies on the JSE over a 20-year period from 1986 to 2006. They follow a style rotation strategy by developing a trading model to predict appropriate switching events. Fama and French (1998) showed that the value premium is a global phenomenon - these researchers focusing on the JSE are no different as value stocks outperformed growth stocks across the entire size spectrum. The research also mirrored the finding of Lakonishok, Shleifer and Vishny (1994) that value style outperforms growth over long periods of time. The influence of size was significant on the results as also found by Reinganum (1999) but it was also evident the value effect occurred across the size spectrum. The findings also concurred with Plaistow and Knight (1986), Van Rensburg (2001) and Van Rensburg and Robertson (2003a, 2003b) who found evidence for the value effect in South Africa.

Basiewicz and Auret (2009) look at JSE stock returns over the period 1992 to 2005 and make a significant contribution by demonstrating the effects of applying restrictions on liquidity and price to mimic constraints that would be placed on portfolios in practice. These restrictions acted as a proxy for transaction costs and significantly reduced the estimates of the size and value premia. This suggested that returns are largely influenced by returns on stocks which would not be included in investors' portfolios in practice - at least not in significant volumes. They also formed value-weighted portfolios in addition to the equally-weighted portfolio approach and found that size and value premium estimates tended to be lower based on value-weighted portfolio formation. However they still confirm the independent existence of a size and PE effect after adjustments for illiquidity.

Using scale mixtures, Janse van Rensburg, Friskin and Sharp (2009) provide a simple model able to capture the subtle differences in the risk structures of size-based portfolios. The study is conducted over the period 1990 to 2005 and analyses the components of the portfolio mixtures in order to contrast the smaller and larger capitalization portfolios. The portfolios are scaled into two small and two large portfolios using log and inverse-log portfolio scales. In doing so, it is shown that the small and large portfolios behave similarly during periods of low volatility, but quite differently during periods of high volatility. It was noted that the portfolios were exposed to a similar degree of risk when in a low-volatility state but during the high volatility state, the smaller capitalization portfolios experienced greater volatility than the larger capitalization portfolios. Comparison of the distributions of the two smaller capitalization portfolios and the two larger capitalization portfolios further adds to the debate around size-effects, which suggests that the return distribution may be related to firm size or portfolio capitalization. Janse van Rensburg et al (2009) however stop at observing variance of distributions and do not proceed further to consider returns between small and large portfolios at different standard deviation levels.

Strugnell, Gilbert and Kruger (2011) build on the observations of Van Rensburg and Robertson (2003) with the aim to establish whether the conclusions of Van Rensburg and Robertson (2003a) are robust and generally valid. The focus on the JSE over the period 1988 to 2007 and conclude that the size effect and value effect are confirmed by the results of their study. They presume the effects are either indicative of some level of market inefficiency or, perhaps more likely, a misspecification of equilibrium pricing models of the CAPM possibly due to the assumption that market covariance alone constitutes rewarded systematic risk. There is also some tentative evidence of a reduction in the size premium over time, but this is not completely conclusive. Van Rensburg and Robertson (2003a) made the observation that beta has an inverse relationship with return which also finds support in this study. It is concluded that their results are not sample-specific as the Strugnell et al (2011) analysis covers a later and longer period.

Hoffman (2012) investigates the presence of stock return anomalies for stocks listed on the Johannesburg Stock Exchange for the period 1985 to 2010. It is concluded that the anomalous behaviour of stocks on the JSE is similar to the behaviour observed by Fama and French on the NYSE - this anomalous return behaviour is also still present after compensating for risk. The study finds support for size, value and momentum effects. This study also provides further evidence against accepting the EMH in its strong or semi-strong form, as the information used is all already publicly available.

It becomes clear from the preceding paragraphs that South African studies have accumulated evidence that style attributes are a strong predictor of returns on the JSE. These trends concur with evidence from the U.S. and other major developed markets discussed in the literature. This provides strong support towards the use of the selected style attributes as driving method behind this study to design sub-portfolios.

2.4 ASYMMETRIES IN CONDITIONAL CORRELATIONS: EMPIRICAL EVIDENCE

2.4.1 Introduction

This section will first explore studies demonstrating correlation asymmetries between international stock markets. It then shifts focus to correlation asymmetries apparent in style characteristics and finally the test results conducted at a cross-sectional portfolio level across various international stock markets. The literature on this subject makes incremental steps over a period of more than 20 years. Some contributions establish newfound benchmarks and result in significant improvements in the research framework. The literature is traced in a chronological manner that includes:

1) Contextual studies of constant volatility,
2) Early studies of asymmetry of international markets,
3) Contextual studies on contagion across markets,
4) Asymmetry in stock returns and style characteristic correlations,
5) Finally, contextual studies on innovations in portfolio management using asymmetry properties,

These are summarised in Table 2-2:

Table 2-6: Summary of empirical studies reviewed

Authors	Year	Classification
Schwert	1989	Contextual – contradiction of constant volatility
Longin and Solnik	1995	Asymmetry: international market correlations
Solnik, Boucrelle and Le Fur	1996	Asymmetry: international market correlations
Longin and Solnik	2001	Asymmetry: international market correlations
Capiello, Engle and Sheppard	2006	Asymmetry: international market correlations
Van Royen	2002	Contextual – contagion effects
Bekaert and Wu	2000	Asymmetry: stock returns correlations
Ang, Chen and Xing	2006	Asymmetry: stock returns correlations
Ang and Chen	2002	Asymmetry: style characteristic correlations
Ferreira and Gama	2010	Asymmetry: industry sector correlations
Hong, Tu and Zhou	2007	Contextual: conditional correlation bias

Campbell, Koedijk and Kofman	2002	Contextual: portfolio construction innovations using asymmetry
Chua, Kritzman and Page	2009	Contextual: portfolio construction innovations using asymmetry

2.4.2 <u>Correlation asymmetries between international stock markets</u>

The foundation for future correlation and variance asymmetry studies came from research by Schwert (1989). The study's objective was to determine the factors causing the change in stock market volatility in the U.S. and to answer the question of why stock volatility changes so much over time. The paper analyses the relation of stock volatility with real and nominal macroeconomic volatility, economic activity, financial leverage, and stock trading activity using monthly data from 1857 to 1987. The standard deviation of monthly stock returns was found to vary from two to 20 percent per month during the study period. Tests for whether differences this large could be attributable to estimation error strongly reject the hypothesis of constant variance. These large changes in the volatility of market returns have important negative effects on risk-averse investors and have important effects on capital investment, consumption and other business cycle variables.

Research before Schwert (1989) did attempt to study movements in aggregate stock market volatility (Officer, 1973; Black and Cox, 1976; Merton, 1980; Abel, 1988) however the literature on "excess volatility" had not addressed the question of why stock return volatility is higher at some times than at others. Relative to the study period of 1857-1987, volatility was unusually high from 1929 to 1939 for many economic variables including inflation, money growth and industrial production. Stock market volatility was also seen to increase with financial leverage, although this factor explained only a small part of the variation in stock volatility. In addition, interest rate and corporate bond return volatility was found to be correlated with stock return volatility. However none of these factors, however, plays a dominant role in explaining the behaviour of stock volatility over time. Instead the author focused on a stock's discount rate – with a stock price being no more than the discounted present value of expected future cash flows to stockholders:

Schwert (1989) went on to argue that at an aggregate level, the value of corporate equity clearly depends on the health of the economy. If discount rates of stocks are constant over time, the conditional variance of security prices is proportional to the conditional variance of the expected future cash flows. Thus, it became plausible that a change in the level of uncertainty about future macroeconomic conditions would cause a proportional change in stock return volatility. If macroeconomic data had to provide information about the volatility of either future expected cash flows or future discount rates, they can then help explain why stock return volatility changes over time.

The research documented firstly evidence that many aggregate economic series are more volatile during recessions. This was particularly true for financial asset returns and for measures of real economic activity. Schwert (1989) offers an interpretation on this evidence that "operating leverage" increases during recessions. Secondly, there is weak evidence that macroeconomic volatility can help to predict stock and bond return volatility. However there is somewhat stronger evidence that financial asset volatility helps to predict future macroeconomic volatility. A reason is that the prices of speculative assets may react quickly to new information about economic events. Thirdly, financial leverage affects stock volatility. When stock prices fall relative to bond prices, or when companies issue new debt securities in a larger proportion to new equity than their prior capital structure, stock volatility increases. However, this effect explains only a small proportion of the changes in stock volatility over time. Fourthly, there is a relation between trading activity and stock volatility. The number of trading days in the month is positively related to stock volatility, as seen in the period 1953-1987. Also, share trading volume growth is positively related to stock volatility.

The paper concluded that the volatility puzzle still remains due to the fact that major episodes in US economic history are associated with larger volatility, such as the Civil War, World War I, the Great Depression, World War II, the Organization of the Petroleum Exporting Countries (OPEC) oil shock and the post-1979 period. The puzzle highlighted by the results is that stock volatility is not more closely related to other measures of economic volatility. For example, the volatility of inflation and money growth rates can be very high during war periods, as is the volatility of industrial production. Yet the volatility of stock returns is not particularly high during war years. Also there were many "financial crises" or "bank panics" during the 19th century in the U.S. that caused very high and volatile short-term interest rates. This study led the way for further research into correlation asymmetries between international stock markets.

Since the seminal work of Levy and Sarnat (1970), Grubel and Fadner (1971) and Lessard (1973), international diversification of equity portfolios has been advocated on the basis of the low correlation between international stock markets. However the covariance between markets could change because the volatility of international markets evolves over time, but also because the interdependence across markets changes. Koch and Koch (1991) considered the correlation of eight markets using daily data for three separate years (1972, 1980 and 1987) and concluded from simple Chow tests that 'international markets have recently grown more interdependent'. Von Furstenberg, Jeon, Mankiw and Miller (1989) reached a similar conclusion using a VAR (Value at Risk) approach for four markets and a very short time period (1986-88). Using high-frequency data surrounding the crash of 1987, King and Wadhwani (1990) and Bertero and Mayer (1990) found that international correlation tends to increase during the stock market crisis. An important question is whether the international correlation increases in periods of high turbulence. International correlation may increase when global factors dominate domestic ones and affect all financial markets.

Longin and Solnik (1995) compare the conditional correlations of seven major country stock markets over the period 1960-1990. They note that the covariance/correlation matrix is an important input for the computation of a trading portfolio. Knowledge about its behaviour, stability and predictability is crucial. It is also of particular importance for testing international pricing theories as misspecification could lead to false conclusions. They argue that progressive removal of impediments to international investment, as well as the growing political, economic and financial integration can affect international market linkages. This could lead to a progressive increase in the international correlation of financial markets reflecting the 'global finance' phenomenon. Their objective is to test the hypothesis of a constant international conditional correlation, investigating various types of deviations. They choose to explicitly model the conditional multivariate distribution of international asset returns and test for the existence of predictable time-variation in conditional correlation for the period 1960-90.

They conclude that the correlation and covariance matrices are unstable over the period with a multivariate GARCH model (with constant conditional correlation) being able to capture some of the evolution in the conditional covariance structure. The volatility of markets also changed somewhat over the period 1960-90 and the proposed GARCH model allows one to capture this evolution in variances. However tests regarding specific deviations lead to a rejection of the hypothesis of a constant conditional correlation. An explicit model of the conditional correlation indicates an increase in the international correlation between markets over the past 30 years. They also find that the correlation rises in periods when the conditional volatility of markets is large.

To further confirm the premise that correlation fluctuates over time, Solnik, Boucrelle and Le Fur (1996) conclude that the correlation between stocks and bonds is irregular over a similar study period as Longin and Solnik (1995). The researchers determine that the benefits of international risk diversification are still robust but the case for international diversification may be overstated when looking at unconditional risk measures. ‘Unconditional’ measures are based on the assumption that variance and correlation between international markets are constant over long periods of time. Investment managers often try to optimise their global asset allocation with a mean-variance optimisation, assuming constant variance and correlation. This results in the unconditional distribution of returns of global portfolios having fatter tails than that of domestic portfolios.

With the knowledge of irregular volatility and decreased benefits of international diversification verified, it is useful to consider both the direction of the asymmetry and the possibility of contagion in international markets. In a follow up study again by Longin and Solnik (2001) the conditional correlation of five countries namely US, United Kingdom (UK), France (FR), Germany (GE) and Japan (JA) are investigated over the period 1959 to 1996. They use a bivariate framework, looking at the correlation of the U.S. market with the other four markets separately - hence four country pairs of US/UK, US/FR, US/GE and US/JA are used. They explicitly model the multivariate distribution of large returns (beyond a given threshold) and estimate the correlation for increasing threshold levels. Under the assumption of multivariate normality with constant correlation, theoretically the correlation of large returns (beyond a given threshold) should asymptotically go to zero as the threshold level increases.

However this is not the case in their estimation based on 38 years of monthly data for the five largest stock markets, at least for large negative returns as the correlation of large negative returns does not converge to zero. Instead it tends to increase with the threshold level, and rejection of multivariate normality is highly statistically significant. On the other hand, the correlation of large positive returns decreases and converges to zero with the threshold level, and the assumption of multivariate normality cannot be rejected. In other words, the study’s results favour the explanation that correlation increases in bear markets, but not in bull markets. With a focus on the tails of the distributions it was concluded that international stock market correlation increases in times of high volatility. These findings should prove disturbing to fund managers as the declines of a bear market, result in most stocks becoming more representative of the overall market making active portfolio management indistinguishable from the broader market index. Contagion corresponds to a situation in which shocks in one country spread to another country in more of a pronounced manner than during quiet times.

With a focus on the 1997 and 1998 Asian and Russian crisis, Van Royen (2002) attempted to uncover whether geographical diversification may have been overstated for that period in the presence of contagion. Identifying contagion and the even more daunting tasks of measuring and predicting it depends on how contagion is defined. The definition of financial contagion is controversial. The traditional definition as noted in the paper is: financial contagion is caused by unexpected and adverse changes in macroeconomic fundamentals. Macroeconomic shocks can be of two forms: an aggregate shock that affects the fundamentals of several countries simultaneously and a shock in one country that leads to changes in the fundamentals in other countries. Both definitions rely on macroeconomic fundamentals as the principal vectors of contagion, and numerous studies are based on macroeconomic tests (Berg and Pattillo, 1998). Most of these analyses have drawbacks as they cannot predict the timing of crises, and they generate a high number of false alarms. This is when a model indicates a crash erroneously when none occurred. These models tend to support the view that crises are explained primarily by real links among countries, such as trade.

Van Royen (2002) challenges these definitions as one can argue that aggregate shocks do not constitute contagion because such shocks are not mechanically transmitted from one country to another - they tend to hit all countries more or less simultaneously. One can also object to the second definition on the premise that the countries in question may be linked by strong trade ties or a common economic policy and therefore be part of the same real economy. Secondly it is noted that the usefulness of empirical studies based on these definitions is questionable. The low frequency of macroeconomic data and the lag in its publication make it unlikely that market participants can use the data to predict the occurrence of sudden market downturns. Also, because macroeconomic variables are widely available and accessible, fundamentals-based crises should have some degree of predictability but this is very difficult to reconcile with anecdotal evidence (such as the Asian crisis which was perceived as unexpected by a majority of investors). The paper sets out to narrow the definition of contagion.

The research points out that when measuring and defining contagion the challenge is to separate how much may be explained by common macroeconomic characteristics, on the one hand, and on the other, how much by sudden high-frequency events that stem from microeconomic factors, such as market news, shifting investor expectations or risk preferences. The definition of contagion can be proposed as: the propagation to another country of a crisis in one country for reasons unexplained by macroeconomic fundamentals. This definition is very much consistent with the notion that contagious episodes appear at random and are unrelated to changes in the real economy. This view is also empirically supported by the fact that some crises cannot be explained by trade links or policy coordination. For example, South Korea had limited links with other Asian economies, yet it was considerably hurt by the Asian crisis

The assumption of the hypothesis tests by Van Royen (2002) was that crisis periods intrinsically differ from quiet periods. The detection of contagion tests focused on measuring the degree of change in the transmission of shocks from one country to another during crises. This view is in contrast to the traditional explanation that shocks do not differ between the two periods because they are transmitted via macroeconomic links, such as trade or economic policy. Evidence of contagion depends on the outcome of an explicit statistical test. The test focuses on pairs of countries. For example if you want to test whether a shock in country *i* triggered a crisis in country *j*, the period is defined over which the crisis occurred in country *i* and a quiet period that preceded the crisis. The null hypothesis is that no contagion was present and the mechanism of shock transmission between the two countries was stable in-between the quiet and crisis periods. The alternative hypothesis is that contagion was present and the mechanism for transmitting shocks between the two countries changed. The results of the study contradict common wisdom that suggests that financial contagion has become widespread. There was little evidence of contagion in the mid-1996 to mid-2000 period of the study and moreover, contagion seemed to be a regional, not a global, phenomenon. There was also little evidence of propagation from one region to another. Based on this study, contagion in Asia tends to propagate to the emerging markets of Europe and to commodity-linked countries. Finally, it was found that measures of contagion possess some degree of predictability and provide evidence that distinct regimes of turbulence exist and that contagion is highly transitory

Capiello, Engle, and Sheppard (2006) analyse the behaviour of global equities and bond indices and uncover similar linkages as Van Royen (2002) in conditional volatilities and correlations. Analysing the conditional estimates of the second moment of these asset returns, evidence indicates an asymmetric phenomenon, where volatility increases more after a negative shock than after a positive shock of the same magnitude. Widespread evidence was documented of asymmetric volatility in the equity series but was absent from the bond returns. However, both equity and bonds showed strong signs of correlation asymmetry with equities showing a stronger response than bonds to joint bad news.

2.4.3 Correlation asymmetries of style characteristics

After concluding the existence of correlation asymmetries at an international stock market level, it is now necessary to explore the correlation of returns one notch lower: at a cross-sectional stock level to determine whether previously discussed style characteristics also register similar irregularities.

Bekaert and Wu (2000) in a volatility study of the Nikkei 225 make a contribution to asymmetric volatility at a firm level where previous research had mainly focused on volatility at an index level (Bae and Karolyi, 1994). Their aim was to document a new phenomenon that helps explain volatility asymmetry at the firm level: covariance asymmetry. The conditional covariance between market and stock returns responds more to negative than to positive market shocks. This makes the volatility feedback effect relatively stronger for positive shocks. Their empirical framework accommodates this possibility and there is evidence of such covariance asymmetry. The findings are that the market is asymmetric in that returns and conditional volatility are negatively correlated. Asymmetric volatility was observed at the firm and market level with negative shocks seen to increase the conditional covariance substantially, whereas positive shocks had a mixed impact on conditional covariance.

In a study by Ang and Chen (2002) on the U.S. market, importance is attached to the scale to the asymmetry and it attempts to determine whether the right or the left tails of the distribution are being affected. They formally define downside correlations as correlations for which both the equity portfolio and the market return are below a pre-specified level. Similarly, upside correlations occur when both the equity portfolio and the market return are above a pre-specified level. Downside correlations in U.S. markets are much larger than upside correlations as presented in Longin and Solnik (2001) and on the downside, portfolios are much more likely to move together with the market. This literature concentrates on documenting covariance asymmetry within a GARCH framework. Their approach of creating portfolios sorted by firm characteristics creates a very different view of the determinants of conditional correlations as compared to previous literature by focusing on the cross-sectional determinants of correlation asymmetry in stock returns. By also employing time-series data, as many observations as possible are included to calculate correlations for events for which there are relatively few observations

The researchers also manage to establish several empirical facts about asymmetric correlations in the U.S. equity market. The level of asymmetry, measured at the daily, weekly, and monthly frequencies, produced sufficient evidence to reject the null hypothesis of a normal distribution. Also to investigate the nature of these asymmetric movements, they examine the magnitudes of correlation asymmetries using portfolios sorted on various characteristics. This is very relevant to this JSE study as Ang and Chen (2002) document that portfolios based on small firms, value firms or low past return firms exhibit greater correlation asymmetry. Significant correlation asymmetry is also found to be present in traditional defensive sectors, such as petroleum and utilities and that riskier stocks, as reflected in higher beta, have lower correlation asymmetry than lower beta stocks.

In a follow up study by Ang, Chen and Xing (2006) it was found that asymmetric diversification is also present for individual stock returns. At an industry sector level, global returns have also exhibited asymmetric characteristics. Ferreira and Gama (2010) document that industries are more correlated in falling markets than rising markets and more importantly industry correlation is positively related to market volatility. During periods of market turmoil, global industry diversification is less able to reduce portfolio risk. Evidence also indicates that the link between correlation and volatility is stronger in rising markets than in falling markets. The negative effect of the increase in volatility for portfolio diversification is most pervasive during up rather than down markets.

2.4.4 <u>Portfolio construction innovations</u>

Portfolio construction is an important field when considering conditional correlations but is not the main objective in relation to this JSE study. However it is still worth broadly touching on a few key papers on the subject.

Beginning with Campbell, Koedijk, and Kofman (2002) evidence is presented that the use of conditional correlations potentially leads to more conservative portfolios than unconditional correlations. The research presented efficient frontiers for allocation between domestic and international stocks. The result concluded that for the same level of risk, the downside-sensitive allocation to international stocks should be lower and a greater portion of overall funds should be allocated to cash. Knowledge of portfolio construction was broadened in the U.S. market with a study by Chua, Kritzman and Page (2009) which focused on a wider class of assets. The asset class is expanded to include hedge fund strategies as its own unique asset class offering with allocation opportunities into such styles as Event Driven, Merger Arbitrage and Equity Market Neutral. Further choice is also provided for the asset class of fixed income with asset allocation opportunities into U.S. government treasuries, high yield and mortgage backed securities opportunities. Also the classic style strategies of value versus growth and small firm versus large firm are offered as an allocation class. A portfolio construction technique was developed whereby asset components exhibit lower correlations on the downside and higher correlations on the upside than mean-variance optimization.

An important conclusion is made by Ang and Chen (2002) when considering the actual value of portfolio diversification. The paper documented asymmetries in the correlations of individual stock returns and conclude that the main attributing factor overstating the value of diversification is the increase of downside correlation. Extending this idea, Hong, Tu, and Zhou (2007) emphasised the importance of asymmetric correlations when considering hedging decisions.

2.5 CONCLUSION

Beginning in the mid-19th century academics have researched the financial metrics of listed companies and regressed these measurements against past share prices. The objective was to identify lasting trends in financial assets over meaningful time periods allowing investors the opportunity to capture excess returns. At the same time, a further body of research developed parallel with the objective of using these excess return anomalies as living proof to debunk the theories of EMH and CAPM. Both fields of research have yielded findings which are largely undisputable and have established characteristics of style as one of the leading predictors of future returns. More emphasis began to be applied to a portfolio's ability to withstand market shocks and a new field of research quickly sprouted which undermined the portfolio's ability to preserve capital during market declines.

Proof emerged that the correlation of financial assets increased in times of market shocks. Research demonstrated this increase in correlation with a coupled increase in volatility using conditional correlations. Attention was now given to the tales of the distribution and the assumption of constant variance over extended periods of time was revoked. Both style and asymmetric correlation are established internationally and from a South African perspective, local style studies have concurred with research on foreign markets. The spirit of this study will be to use previous literature on international markets and to apply similar methodologies to construct portfolios from style characteristics and then determine whether the correlation profiles of the portfolios have degrees of symmetry which are useful to portfolio construction decisions.

Given the success of the above-mentioned studies, a similar methodology will be utilised, where possible, to ensure the research provides equally satisfying results. This study is feasible given the “spirit” of the research is similar, thus the likelihood of gathering similar results are high.

CHAPTER THREE

METHODOLOGY (RESEARCH DESIGN AND METHODS)

3.1 INTRODUCTION

The correlation measurement is conditional upon the sample portfolio and the market registering similar standard deviation movements in the same direction away from the mean. The objective is to use the correlation measurement to convey the closeness with which the sample portfolio tracks the market during broad market gains and declines. The procedure involves measuring the downside correlations at specific exceedance levels (conditional correlation levels). An exceedance level is simply a standard deviation measurement calibrated at pre-specified levels, and the correlation in turn registered at these pre-specified levels. Downside correlations are correlations for which both the style portfolio and the market return are below a pre-specified level known as an exceedance level. Correlation at an exceedance level ϑ is defined as the correlation between two variables when both variables register increases or decreases of more than ϑ standard deviations away from their respective means. For example $\vartheta = -1$, the exceedance correlation between an equity portfolio and the market portfolio is calculated on the specific set of data when both the equity portfolio and market portfolio are more than 1 standard deviation below their empirical means. The correlation between these two variables is defined as:

Equation 3-1:

$$\overline{\rho}(\vartheta) = \begin{Bmatrix} \hat{\rho}(\vartheta, \infty, \vartheta, \infty) = corr(\tilde{x}, \tilde{y} | \tilde{x} > \vartheta, \tilde{y} > \vartheta; \rho) \ldots if \, \vartheta \geq 0, \\ \hat{\rho}(-\infty, \vartheta, -\infty, \vartheta) = corr(\tilde{x}, \tilde{y} | \tilde{x} < \vartheta, \tilde{y} < \vartheta; \rho) \ldots if \, \vartheta \leq 0. \end{Bmatrix}$$

where

ϑ	is the exceedance level and determines the cut-off points for the conditioning sample which is expressed as multiples or fractions of standard deviations from the observed mean values.
$\overline{\rho}(\vartheta)$	is the empirical exceedance correlation.
$\tilde{x}, \tilde{y}$	are the pairs of standardised observations.
$(\tilde{x}, \tilde{y} \| \tilde{x} > \vartheta, \tilde{y} > \vartheta; \rho)$	are the subset of observations for $\vartheta \geq 0$.

$(\tilde{x},\tilde{y} \vert \tilde{x} < \vartheta, \tilde{y} < \vartheta; \rho)$	are the subset of observations for $\vartheta \le 0$.

For $\vartheta =$ 0 both $corr(\tilde{x},\tilde{y} | \tilde{x} > 0, \tilde{y} > 0; \rho)$ and $corr(\tilde{x},\tilde{y} | \tilde{x} < 0, \tilde{y} < 0; \rho)$ are calculated. These correlations would be the same for a symmetric distribution but may differ in the data hence both $\vartheta \ge 0$ and $\vartheta \le 0$ are considered. Ang and Chen (2002) develop a model using exceedance calculations. When calculating the exceedance correlation, ϑ determines the cut-off points for the conditioning sample. These cut-off points can be expressed in multiples or fractions of standard deviations from the observed mean values. To jointly look at correlations over upside and downside movements, the exceedance levels are $\theta = [-1.5, -1.0, -0.5, 0.0, 0.0, 0.5, 1.0, 1.5]$.

The repeated zero is necessary in the exceedance level array as $corr(\tilde{x},\tilde{y} | \tilde{x} < 0, \tilde{y} < 0)$ $corr(\tilde{x},\tilde{y} | \tilde{x} > 0, \tilde{y} > 0)$ calculated. The positive exceedances will be $\theta^+ = [0.0, 0.5, 1.0, 1.5]$ to look at correlations on the upside. The negative exceedances will be $\theta^- = [-1.5, -1.0, -0.5, 0.0]$ to look at correlations on the downside.

In the study conducted by Ang and Chen (2002), the authors focus on the observations lying in the tails to estimate extreme correlations. The research reveals that the correlations between domestic equity portfolios and the aggregate market are greater in downside markets than in upside markets. The various degrees of magnitude of asymmetry can be summarised and the individual portfolios ranked according to correlation levels.

Table 3-1 shows the sub-samples occurring at each exceedance level. The return data is standardised for both the sub-portfolio and the market (J200) on a daily basis. Each exceedance level is a calibrated standard deviation increment from the mean of the sub-portfolio and the market. As the data has been standardised the scale of the moves are the same for the sub-portfolio and the market. Each trading day the respective standard deviations are assessed whether they have simultaneously moved into the same exceedance level. The largest samples can be found at the exceedance levels <0σ and >0σ which are closest to the mean. Naturally the further we move away from the mean the smaller the samples become. The main reason is that large daily moves in the overall market are rare, especially very large moves occurring at the extremities of the tails. The exceedance levels of <(2) σ and >(2) σ were deliberately included in Table 3-1 to demonstrate the very small sample size that was collected at these extreme levels. Hence it was decided to only consider the exceedance levels up to +1.5σ and -1.5σ to maintain the accuracy of the results.

Table 3-1: Portfolio sub-sample at each exceedance level

	Low-DY	High-DY	Low-PE	High-PE	Small firm	Large firm	Low-Vol	High-Vol
<(2)σ	22	36	19	38	15	43	10	40
<(1.5)σ	52	80	47	86	33	103	33	91
<(1)σ	139	204	130	205	99	229	110	211
<(0.5)σ	363	435	344	460	289	496	302	459
<0σ	767	881	776	893	694	942	708	892
>0σ	783	961	754	968	658	1020	684	976
>(0.5)σ	291	464	279	461	220	514	242	460
>(1)σ	101	176	97	148	67	194	67	167
>(1.5)σ	39	70	33	56	16	76	19	64
>(2)σ	16	28	9	23	5	25	6	23

Even though conditional correlation is highly effective in isolating the tails of the distribution, the necessary attention must be given to the potential pitfalls of using sub-sample data. The main problem is that when data is conditioned into sub-samples at the various exceedance levels it cannot be assumed that the data points will remain completely independent. The grouping of the data will resemble attributes of a 'cluster'. Secondly as the daily returns will be sorted into their appropriate standard deviation style portfolio groupings, these groupings will need to appropriately 'notify' the model when the conditional criteria have not been met. To demonstrate this point further, for example if a model is run to test for symmetric correlation between the daily return groupings of the +1 versus the -1 standard deviations, it is important to incorporate a dummy variable as an interaction term. An appropriate method is to format the daily returns into intervals with the use of the dummy variable zero. The use of zero is to create a boundary between segments, a breakpoint. A 'broken-stick regression', formally referred to as a piecewise linear regression can then be used to measure the correlation symmetry. The dummy variable has no statistical significance so will not be reflected in the results of Chapter 4.

This section will begin with an overview of the GARCH model as a potential application followed by a review of the Piecewise Linear Regression (PLR). The conclusion and choice of model will be discussed under section 3.6.

3.2 INDEPENDENCE OF RESIDUALS

Both the GARCH-M and PLR model require the assumption to be met of independent residuals and for this purpose the analysis of residuals will be considered under this section. The residuals are shown through scatterplots in Figures 3-1 to 3-8. From the figures it can be concluded that there is no correlation of residuals around any specific level and that residuals are independent from each other.

Figure 3-1: Low DY portfolio residuals

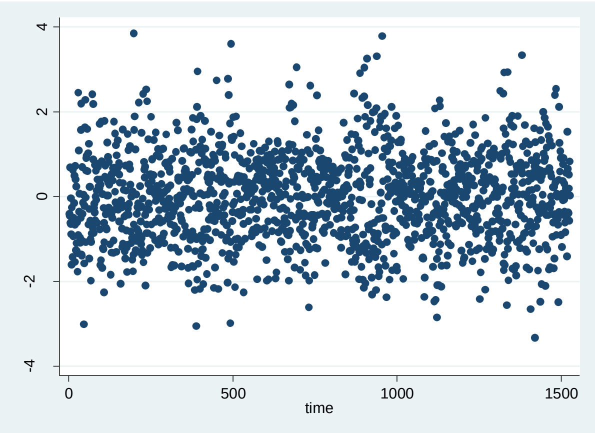


Figure 3-2: High DY portfolio residuals

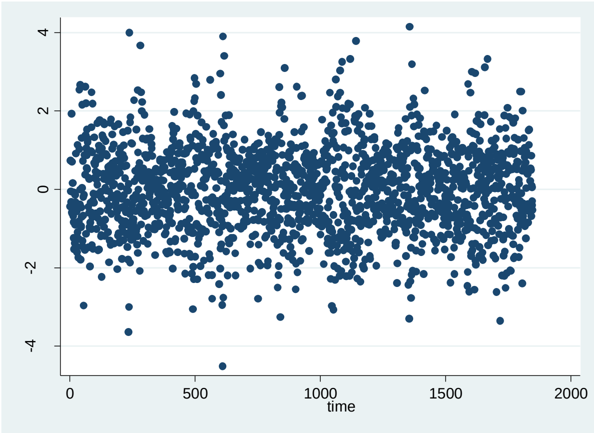


Figure 3-3: Low PE portfolio residuals

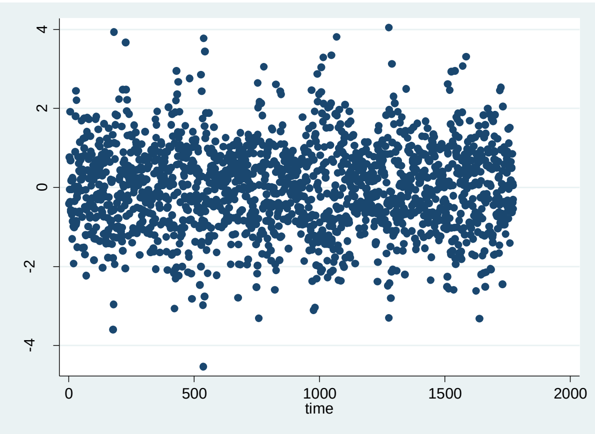


Figure 3-4: High PE portfolio residuals

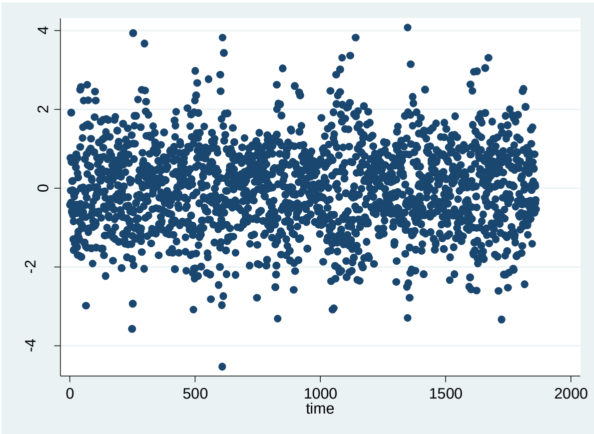


Figure 3-5: Small portfolio residuals

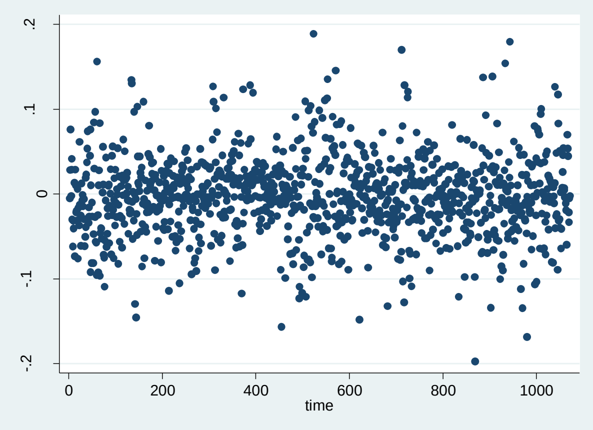


Figure 3-6: Large portfolio residuals

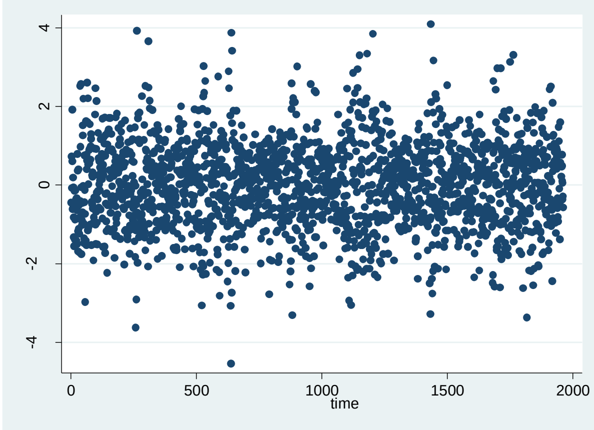


Figure 3-7: Low volume portfolio residuals

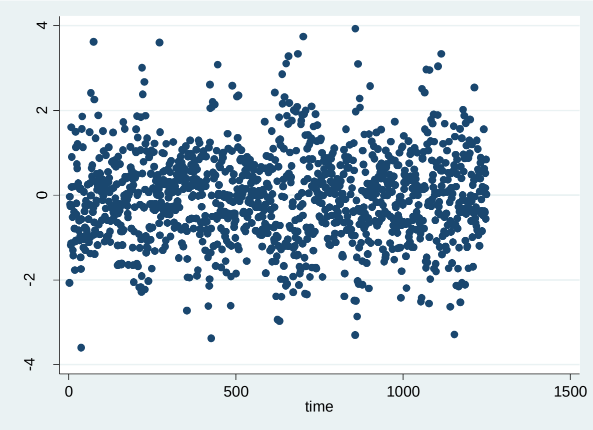
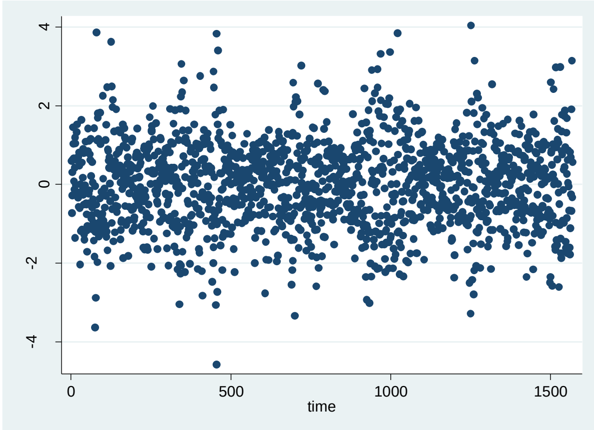


Figure 3-8: High volume portfolio residuals



3.3 GENERALISED AUTOREGRESSION CONDITIONAL HETEROSKEDASTICITY (GARCH) MODEL

When considering how much one variable will change in response to a change in some other variable it is important to forecast and analyse the size of the errors of the model. The least squares model in its primary form assumes that the expected value of all error terms, when squared is the same at any given point. This assumption is called homoscedasticity. ARCH/GARCH models focus on this assumption. Data in which the variances of the error terms are not equal, in which the error terms may reasonably be expected to be larger for some points or ranges of the data than for others, suffer from heteroskedasticity. ARCH and GARCH models treat heteroskedasticity as a variance to be modelled and a prediction is computed for the variance of each error term. Engle (1982) was the first to propose an Autoregressive Conditional Heteroskedasticity (ARCH) model. The researcher let the weights used to estimate future volatility, taken from previous period volatility, be the parameters to be estimated. Thus the model allowed the data to determine the best weights to use in forecasting the variance. The main benefit of using the typical GARCH is that it allows for a simple fit to the data.

Bollerslev (1986) introduced a generalization of the ARCH model, known as GARCH. The model also uses a weighted average of past squared residuals, but never allows the declining weights to go to zero. The GARCH (1, 1) is the simplest and most robust of the family of volatility models. A GARCH (1, 1) can be generalized to a GARCH (p, q) model, a model with additional lag terms. The GARCH (2, 2) model was introduced by Engle and Lee (1999) and contains additional lags and allows for both fast and slow decay of information. Bollerslev (1990) again used the GARCH model to document conditional covariance under the assumption of constant conditional correlation (CCC) over the sample period. Further covariance studies followed by Koutmos and Booth (1995); Booth, Martikainen, and Tse (1997); Scruggs (1998), and Christiansen (2000) but all maintained Bollerslev's approach of constant correlation coefficients. This approach greatly simplifies estimation but the hypothesis is neither theoretically correct nor is the empirical evidence justifiable. Strides were made by Kroner and Ng (1998) with the introduction of a modified version of the multivariate (GARCH) model. GARCH is a more flexible class of multivariate conditional variance model as it removes the assumption of constant correlation coefficients. Further applications by Bekaert and Wu (2000) and Glabadanidis (2009) build on this model.

ARCH and GARCH models originally ignored information on the direction of returns. Only magnitude mattered. However, market declines can forecast higher volatility than comparable market increases do. A variety of asymmetric models were established to remedy this problem. Namely the Exponential GARCH (EGARCH) model of Nelson (1991); the Threshold ARCH (TARCH) model by Rabemananjara and Zakian (1993) and Glosten, Jaganathan and Runkle (1993) and finally a collective comparison by Engle and Ng (1993) was conducted. Cappiello, Engle, and Sheppard (2006) then proposed a generalization of the dynamic conditional correlation (DCC) GARCH model of Engle (2002) whereby the univariate volatility parameters of a standard GARCH (1,1) model are modified to accommodate conditional asymmetries in correlations.

However, with all these developments the assumption of constant conditional correlations remains the major shortcoming of ARCH and GARCH models. Additionally, when examining several assets simultaneously, questions arise whether the volatility of one asset influence the volatility of another

More specifically, the volatility of an individual stock is influenced by the volatility of the market as a whole. This leads to multivariate testing whereby both volatility and correlation are to be investigated. A more robust model is required to measure conditional correlations such as the Dynamic Conditional Correlation (DCC) form of the GARCH model. However the use of DCC GARCH is not always possible due to data constraints. For a mathematical representation of the GARCH model one can refer back to the study by Bollerslev (1986).

Certain studies have analysed the patterns of asymmetries in the covariance of stock returns in domestic equity portfolios within a GARCH framework. The papers documenting asymmetric covariance in multivariate GARCH models are Ball and Kothari (1989), Braun, Nelson and Sunier (1995), and Cho and Engle (2000). In these studies covariance asymmetry is defined as the increase in conditional covariance resulting in past negative shocks in returns. These studies did provide significant literature to the topic of the volatility and correlation of financial asset returns but were still carried out under the assumption of constant conditional correlation between the market and shares over time.

One of the negative aspects of the GARCH family of models is that they are sensitive to limited data sets. As this study focuses on a shorter period of 10 years as compared to other studies [Longin and Solnik (2001) consider a data period of 1959-1996 (37 years); Ang and Chen (2002) have a data period from 1963-1998 (35 years); Hong, Tu and Zhou (2007) data period is 1965-1999 (34 years)] it is important that the thresholds used for the estimation of the model capture enough return data to make the results statistically significant and ensure the model fits the distribution as best as possible. Under a GARCH framework, choosing a high exceedance level, such as all conditional returns above 1.5σ's leads to very few observations above this exceedance level and the GARCH model will imply inefficient parameter estimates with large standard errors. This is noted in Table 3-1 by the very few observations occurring at $>2\sigma$ and $<2\sigma$ so to optimize the efficiency of the GARCH test the positive tail will be considered as one complete range and the negative tail as another complete separate range.

Using asymmetric GARCH models, previous researchers focused on the asymmetric movements of leverage-sorted portfolios of Japanese stocks (Bekaert and Wu, 2000), and size-sorted portfolios of U.S. stocks (Kroner and Ng, 1998; Conrad, Gultekin and Kaul, 1991). This JSE study will use the GARCH-in-mean (GARCH-M) model used by Ang and Chen (2002) to evaluate the magnitudes of correlation asymmetries in portfolios sorted on various style characteristics. The GARCH-M will be fitted at each exceedance level and any doubts around automatic clustering have been removed by the independence of residuals observed in Section 3-2. The GARCH-M model does not assume constant correlation through both the negative and positive tails and allows for asymmetric movements between upside and downside movements in returns.

Due to the increased estimation errors that the GARCH-M model faces when considering smaller data sets, the PLR model will be considered as a possible supplement under section 3.3. The PLR model is able to handle reduced data sets therefore it can be considered for the correlations at each exceedance level where the GARCH-M model could only be used for comparing the left versus the right tails in their entirety. Before the PLR model can be considered as a supplement it is important to evaluate the model against the GARCH-M model. This exercise is conducted under section 4.3.3 whereby both models are run on the same 10-year data set. The overall outcome of the model comparison will be discussed in detail under section 4.3.3 but in summary both models identify very similar asymmetric trends in the tails of the style portfolios. In addition there is also very little difference in the correlation coefficients between each model.

3.3.1 GARCH model assumptions

The GARCH framework requires residuals to be independent. This assumption was tested in Section 3.2 and it can be concluded that residuals are independent. The second assumption for an effective GARCH model is normally distributed residuals. The PLR model also requires independence of residuals hence this assumption has also been tested in conjunction with the PLR model. The normality tests can be found under Section 3.4.1 in the histograms of Figures 3-9 to 3-16. This assumption is satisfied as the residuals reflect normality for each style portfolio.

3.4 PIECEWISE LINEAR REGRESSION

The measurement of conditional correlation makes it necessary to allocate the data into ‘buckets’ at the various exceedance levels. Each bucket is grouped according to standard deviation and within each bucket it is also necessary to sort the data in time series. It is known that the sets of observations sitting within each sub-sample came from certain standard deviation pairs in a specific order in time. This is known as longitudinal or panel data. It would be incorrect to use a standard regression as this approach assumes the returns at each trading day are independent. The returns would have been independent in normal, unconditioned time series format, but after conditioning into sub-samples they are no longer independent. The conditioning reduces this independence, for example, it is likely that daily returns falling within the +1 standard deviation group would have moved in a similar manner to justify their inclusion into that category in the first place - exhibiting similar features and characteristics. The bias from conditioning the data at various standard deviation levels and the exclusion of trading days, where the market and the portfolio are not registering the same standard deviations away from their respective means, results in 'clustering' within the sub-samples.

This clustering may result in the daily returns in a specific exceedance level impacting the predictor or outcome variables. It is necessary to use a Fixed Effects (FE) approach to control for this effect. FE removes the effect of those time-invariant characteristics from the predictor variables so the predictors' net effect can be assessed. An important assumption of applying an FE model is that the time-invariant characteristics are unique to the individual exceedance level and should not be correlated with other exceedance level characteristics[4]. Each standard deviation grouping is different therefore the sub-sample's error term and the constant (which captures individual characteristics) should not be correlated with the others. If the error terms are correlated then a FE model is not suitable since inferences may not be correct. This relationship would then be better modelled by a Random Effects (RE) model. In addition goodness of fit tests are conducted under sections 4.3.1 and 4.3.2 for the PLR and GARCH-M models. For a mathematical representation of the PLR model refer to Hamilton (1994).

The Hausman test determines the choice of the FE or RE model. The two goodness of fit tests used when analysing the PLR model are an F-test for the Fixed Effect (FE) approach and a Chi-squared test for the Random Effect (RE) approach. The Hausman test first determines the most suitable approach, that is whether a FE or a RE framework should be used. A p-value of below 5% results in the choice of a FE approach and above 5% the RE approach must be used. The Hausman test results are shown in Table 3-2 and are all in favour of a FE approach for the PLR model and as no RE approach was chosen by the Hausman results there are no results reported for the Chi-squared output (not applicable). Also all the p-values of the F-test are below 5% indicating the model fits the data well. The exceedance levels (standard deviation levels) are included as c_1 through c_4 with the

[4] Panel Data Analysis Fixed & Random Effects, http://dss.princeton.edu/training/

Hausman test results in Table 3-2. There is only one circumstance where the F-test p-value is above 5% and that is at c_4 for the Low-PE portfolio which registers a p-value of 0.0794.

Table 3-2: Hausman test results[5]

Portfolio	c1 = 0.0	c2 = 0.5	c3 = 1.0	c4 = 1.5
Size-sorted portfolios				
Large firm				
Hausman test p-value	0.0000	0.0000	0.0000	0.0008
Choice of model	FE	FE	FE	FE
F test p-value for FE model	0.0000	0.0000	0.0000	0.0000
Chi-squared p-value for RE model	N/A	N/A	N/A	N/A
Small firm				
Hausman test p-value	0.0000	0.0000	0.0000	0.0001
Choice of model	FE	FE	FE	FE
F test p-value for FE model	0.0000	0.0000	0.0000	0.0018
Chi-squared p-value for RE model	N/A	N/A	N/A	N/A
PE-sorted portfolios				
High-PE				
Hausman test p-value	0.0000	0.0000	0.0000	0.0001
Choice of model	FE	FE	FE	FE
F test p-value for FE model	0.0000	0.0000	0.0000	0.0000
Chi-squared p-value for RE model	N/A	N/A	N/A	N/A
Low-PE				
Hausman test p-value	0.0000	0.0000	0.0000	0.0000
Choice of model	FE	FE	FE	FE
F test p-value for FE model	0.0000	0.0000	0.0000	0.0794
Chi-squared p-value for RE model	N/A	N/A	N/A	N/A
DY-sorted portfolios				
High-DY				
Hausman test p-value	0.0000	0.0000	0.0000	0.0000
Choice of model	FE	FE	FE	FE
F test p-value for FE model	0.0000	0.0000	0.0000	0.0000
Chi-squared p-value for RE model	N/A	N/A	N/A	N/A
Low-DY				
Hausman test p-value	0.0000	0.0000	0.0000	0.0000
Choice of model	FE	FE	FE	FE
F test p-value for FE model	0.0000	0.0000	0.0000	0.0407
Chi-squared p-value for RE model	N/A	N/A	N/A	N/A
Volume-sorted portfolios				
High-Volume				
Hausman test p-value	0.0000	0.0000	0.0000	0.0225
Choice of model	FE	FE	FE	FE
F test p-value for FE model	0.0000	0.0000	0.0000	0.0000
Chi-squared p-value for RE model	N/A	N/A	N/A	N/A
Low-Volume				
Hausman test p-value	0.0000	0.0000	0.0000	0.0028
Choice of model	FE	FE	FE	FE
F test p-value for FE model	0.0000	0.0000	0.0000	0.0135
Chi-squared p-value for RE model	N/A	N/A	N/A	N/A

Fixed Effects model approach is denoted as FE.
Random Effects model approach is denoted as RE.

[5] Source: I-net and author's own estimates

A Piecewise Linear Regression (PLR) was used by Ball, Kothari and Nikolaev (2013) to examine the reaction of a cross section of companies to economic shocks, absorbed via a news stream, and the dependence of these companies' reactions to market and political variables. PLR was used as the data examined could only exhibit a single state, true or false, but not both at any given point in time. The various states of the closing price of the market are mutually exclusive and cannot record two states simultaneously, for example, the closing price on Tuesday the 11th November 2014, cannot close both up 1% and down -2% on the same day. This suits the case of this study well as the effect of the independent variable (the market portfolio) on the dependant variable (style portfolio) needs to be documented for both market positive and market negative states. The market positive state can only register a return value on a specific trading day if the standard deviation moves of the market and style portfolio are of both the same magnitude and positive direction from their respective means. Due to the return data being conditioned into panel format, the market negative state would be zero on this very same day, as the outputs are mutually exclusive. The exceedance level range considered for the PLR model will be -1.5σ to +1.5σ for the 10 year period. The same data range will be considered for the GARCH model explained in section 3.3.

3.4.1 PLR model assumptions

The first assumption for PLR analysis from Montgomery, Peck and Vining (2012) is the independence of the residuals (which are the actual-*y* minus predicted-*y* values), meaning the value of one residual is unrelated to the value of the next. This assumption was considered and satisfied under the independence of residuals Section 3.2.

The second assumption is that the residuals exhibit normality. This means the error in the model prediction, which is the distribution of the residuals, should appear to be a bell-shaped curve (a normal distribution) with many "average" sized residuals and fewer large and small residuals. Normality of error terms is observed through Figures 3-1 to 3-8.

Figure 3-9: Low PE portfolio errors[6]

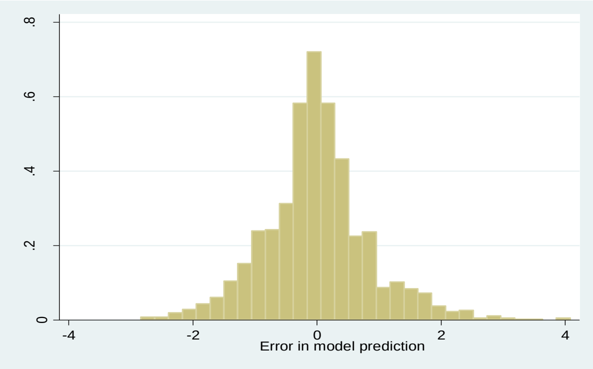


Figure 3-10: High PE portfolio errors[7]

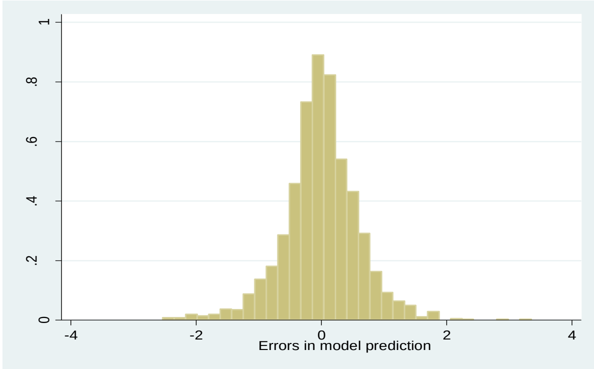


Figure 3-11: Low DY portfolio errors[8]

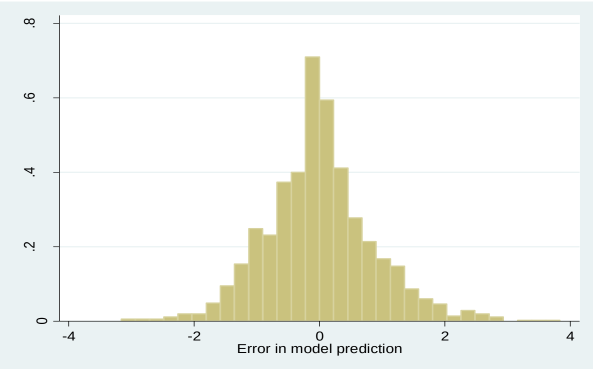


Figure 3-12: High DY portfolio errors[9]

Figure 3-13: Small portfolio errors[10]

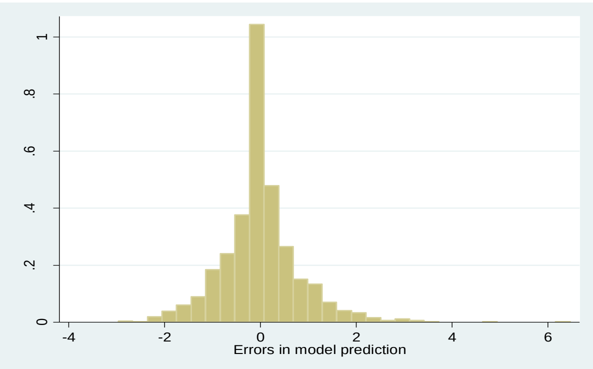
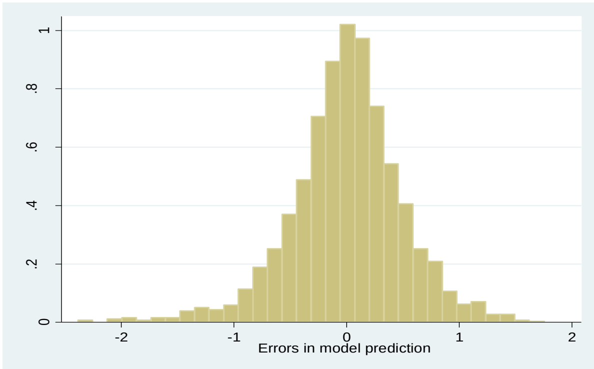


Figure 3-14: Large portfolio errors[11]



[6] Source; I-net and author's own estimates
[7] Source; I-net and author's own estimates
[8] Source; I-net and author's own estimates
[9] Source; I-net and author's own estimates
[10] Source; I-net and author's own estimates
[11] Source; I-net and author's own estimates

Figure 3-15: Low volume portfolio errors[12]

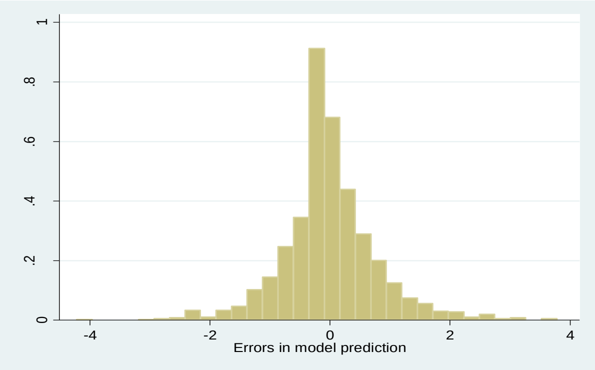
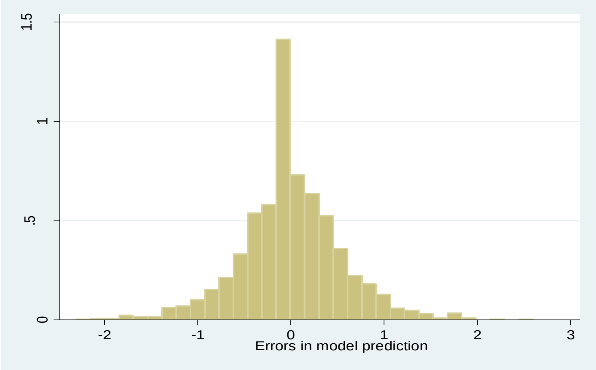


Figure 3-16: High volume portfolio errors[13]



The third assumption is that residuals have homogeneous variance, with the variability of the residuals between and within the fitted segments being approximately constant. Table 3-3 shows a constant variability of residuals between the within and interclass groups. This assumption was also considered through the use of the Hausman test. Before the FE or RE approach to the PLR was applied, the Hausman test helped determine which approach was most suitable for the data by considering the independence within groups. The Hausman results in Table 3-2 are all in favour of the FE approach. An important assumption of the FE model is that those time-invariant characteristics are unique to the individual and should not be correlated with other individual characteristics. If the error terms are correlated, then FE is not suitable since inferences may not be correct and one needs to model that relationship (probably using the RE approach), this is the main rationale for the Hausman test.

12 Source; I-net and author's own estimates
13 Source; I-net and author's own estimates

Table 3-3: Variance of residuals[14]

Standard deviation of residuals			
Portfolio	within groups	intraclass	difference
Low DY	0.8692	0.6725	0.1967
High DY	0.4524	0.5531	-0.1006
Low PE	0.7918	0.5952	0.1966
High PE	0.4311	0.4050	0.0261
Large	0.2945	0.2916	0.0029
Small	0.7028	0.5308	0.1720
Low volume	0.6735	0.5267	0.1468
High volume	0.3092	0.2748	0.0344

The PLR model is given by:

Equation 3-2

$$y_{\text{style return}_i} = \beta_{\text{positive market}}.X_{\text{positive return}_i} + \beta_{\text{negative market}}.X_{\text{negative return}_i} + \propto + \varepsilon$$

where:

$y_{\text{style return(i)}}$	is the return derived from a style portfolio on specific trading day i.
$\beta_{\text{positive market}}$	is the correlation coefficient of the market positive variable.
$X_{\text{positive return(i)}}$	is the return on day i of the market if positive correlation criteria is satisfied
	otherwise zero (dummy variable) if positive conditional correlation is not satisfied.
$\beta_{\text{negative market}}$	is the correlation coefficient of the market negative variable.
$X_{\text{negative return(i)}}$	is the return on day i of the market if negative correlation criteria is satisfied
	otherwise zero (dummy variable) if negative conditional correlation criteria is not satisfied.
$\propto$	Constant
ε	error term

The mutual exclusivity of the dummy variables implies that if X_1 is a positive return then the X_2 dummy variable will equal zero and the opposite occurs for negative returns. It can be argued that the dummy variable makes this a univariate application of the GARCH model however it can also be technically considered a bivariate application. This is however just semantics as the dummy variable does not have any impact on the results. Intuitively if one is examining conditional correlations at the extreme ends of a distribution it may be worthwhile considering a non-linear model as a method of approximation. Longin and Solnik (2001) study the conditional correlation structure of international equity returns using the extreme value theory. The theory derives the

[14] Source; I-net and author's own estimates

asymptotic distribution of the conditional tail correlation. The benefit of this method is that the asymptotic results hold for a wide range of parametric distributions of returns. However it is only able to provide asymptotic results which is limiting. As the extremities of the tails are being examined, the mean of the distribution of the exceedance level at -0.5σ would be different to the mean found towards the end of the tail at -1.5σ – extreme value theory takes this into consideration. However the PLR model also takes this into consideration due to the "broken stick" element of its nature. The PLR approach isolates the segments of the distribution falling into each exceedance level and runs a regression. This avoids extreme outliers from influencing the overall distribution and skewing the correlation results. The PLR model is the favoured approach in this study as it copes well with reduced data sets while maintaining the estimation accuracy.

3.5 SAMPLING AND DATA COLLECTION

One of the key objectives of the research is to test and analyse a complete data set. Thus the sample contains stocks from all sectors of the JSE. The primary sources of return data used in this study are from I-Net Bridge (henceforth, I-Net). The ratios will be drawn from audited financial year-end reports and interim results were ignored. The study will be over the 10 year calendar period which will start on 31 December 2002 and end on 31 December 2012. By starting the study period at the end of December 2002, it will allow the portfolios to be formed by the close of the year and enter the 2003 calendar with all the investor's holdings already in place. This avoids any rebalancing from taking place in the new year. This decade covers the bottoming of the dot com bubble in 2003 as referenced by the NASDAQ index closing values; the boom and bust of the United States housing bubble where housing peaked in 2006 and then continued to decline until bottoming in 2012[15]; the proceeding Great Recession[16] of 2007 to 2009 and finally the Quantitative Easing (QE) [17] programs adopted by the large central banks namely the United States Federal Reserve, Bank of England (BoE), Bank of Japan (BoJ) and the European Central Bank (ECB).

Significant studies have been conducted on style factors by Van Rensburg and Robertson (2003) and further supported by Auret and Sinclaire (2006). This study will adopt the same perspective on

[15] Source: ^In *Wikipedia*. Retrieved February 28, 2014, from http://www.standardandpoors.com/indices/sp-case-shiller-home-price-indices/en/us/?indexId=spusa-cashpidff--p-us.The report states that the Housing Composite Index hit new lows.
[16] Source: Rampell, C. (2009, November, 3). Great Recession: A Brief Etymology. *New York Times*.
[17] Source: Loose thinking (2009, October 15). *The Economist*. Retrieved from http://www.economist.com/node/14649284.

independent variables of these previous studies. Hence, the analysis will be performed on the 3 most significant variables reported by Van Rensburg and Robertson (2003a) and also with the addition of volume traded. In this study there will be four indicators used as independent variables, namely:

- Size - the market value of the company which is calculated as [ln (number of ordinary shares outstanding times the price per share)]
- PE – the price-to-earnings ratio is calculated as [price per share / earnings per share]
- Volume – the number of shares traded per day
- DY – dividend yield is calculated as [(ordinary dividends / ordinary shares) / price per share]

The empirical studies on style anomalies and asymmetric correlations discussed in Chapter Two used daily closing return series data in the respective investigations. Daily data will also be the frequency of choice for this study. The J200 index will be used in daily frequency as the proxy for the market. The J200 consists of the top 40 tradable shares on the JSE ranked by market capitalisation. The PE and DY ratios incorporate a daily closing price component in their calculation as well as a static financial statement statistic. The daily closing prices of companies will be used in conjunction with the latest earning per share statistic, taken from the company's latest audited financials, and declared dividends. Declared dividends will be the most up to date distribution by the company, including any interim or special dividends for the period. The size and volume ratios are measured in a daily frequency form and then these ratios are ranked on an individual share basis and sub-portfolios created according to a median split. In practical terms this will allow portfolios to be assembled on the last trading day of each year with a buy and hold strategy following in the next year.

Returns are calculated according to Equation 3-3

$$R_{it} = ln\left(\frac{P_{\mathrm{i;t}} - P_{\mathrm{i;t-1}}}{P_{\mathrm{i;t-1}}}\right)$$

R_{it}	is the return of stock i on day t
$P_{\mathrm{i;t}}$	is the price of share i on day t
$P_{\mathrm{i;t-1}}$	is the price of share i on day t -1 (closing price on previous day)

In the current daily return data there are distortions due to non-trading days. There are two prescribed methods for dealing with non-trading days. The first is a technique of simulation suggested by Glezakos, Merika and Kaligosfiris (2007). This involves calculation of a specific share price by simulation on a non-trading day. The second method is the elimination of non-trading days suggested by Chowdhury (1994) and Chang, Nieh and Wei (2006). Simulation may inflate or deflate stock returns on a non-trading day and does not guarantee accurate calculation. The sample size also spans a 10 year period and should be sufficiently robust not to affect empirical findings by eliminating non-trading days. For these reasons the study will eliminate non-trading days in the data. To appropriately account for differences in volatilities each time series will be standardized. This follows the approach adopted by Chua, Kritzman and Page (2009) in a similar study of conditional correlations. Also, whenever dealing with standard deviation it is important to standardize the data, as the results may be influenced by difference in magnitude or scale of stocks versus an index. The data will also be standardized to account for any differences in volatilities and to take out extreme outliers. Each time series will be standardized on the same basis as Chua, Kritzman and Page (2009) which is as follows: (x – mean)/standard deviation

A thin trading filter is applied to the data to remove stocks where the average monthly trading data is less than 0.01% of ordinary shares in issue of the previous month. This approach was adopted from the Van Rensburg and Robertson (2003a) study and ensures that the stocks remaining in the data set, traded at least once during the month. The stocks making up the style portfolios will be rebalanced annually. The rebalancing will take place according to the daily closing data of the penultimate trading day of the year. The logic of this move was to simulate the portfolio rebalancing challenges faced by fund managers. This will then allow portfolio managers to use the last trading day of the year to rebalance the style portfolios before the start of the new year. For added accuracy, the rebalanced portfolios will include the return between closing price of the last day of trade of the previous year and the closing price of the first day of trade of the new year. Companies will be ranked in ascending order according to style attribute. A median split will then be used to allocate companies to each style factor portfolio. Looking at the size factor, companies falling in the lower half of the median split will be considered small cap stocks. Companies falling in the upper half of the median split will be considered large cap stocks. As for the PE portfolio, companies in the lower half of the median split will be considered value stocks and companies in the upper half will be considered growth stocks. The remaining style factors of DY and Volume, these factors will produce portfolios in a similar manner based on low and high ratios. A median split was the preferred choice of ranking portfolios, as the JSE is a comparatively small market when compared to other developed markets. If the JSE had for example the same number of listed companies as traded on the US market, a quartile or percentile split could be motivated. Henceforth, taking the size of the JSE into consideration, the median split was the most practical approach to portfolio design.

The daily returns from each company making up the portfolio were averaged on an equally weighted basis to derive a portfolio return. The main reason for the choice of equal weighting over value weighting is due to the top-heavy nature of the JSE. By market capitalisation alone, the top 5 shares on the JSE would skew this weighting and the portfolio would all most entirely represent the top 5 shares[18].

The ratios used will be drawn from year-end financial statements, ignoring interim results. The ratios have been lagged so the data from any particular year-end are matched with returns for the following year. This method was successfully implemented by Auret and Sinclaire (2006) and allows sufficient time for all financial statement information to filter into the market and hence the specific company share prices they represent. The problem of survivorship bias will be addressed by the sample showing missing values once the share has been de-listed. Look-ahead bias of Banz and Breen (1986) will be alleviated as the ratios mentioned above are produced six months after the financial year-end.

3.6 METHOD

This study will conduct a brief overview of descriptive statistics before any major tests are conducted. The return data will be first allocated to its various style sub-samples within each style factor before descriptive statistic test are conducted. The reason for this choice is that it is more beneficial to review descriptive statistics on sub-samples than the overall sample. By example, the sub-samples within the size factor will be the daily returns of the stocks making up the large stock portfolio versus the corresponding small stock portfolio. By first using the predefined filter of a median split to allocate stocks to either the upper or lower sub-sample within each style portfolio, then interpreting the descriptive statistic findings, this may avoid a sub-sample from dominating the overall sample population and skewing the descriptive statistics.

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[18] Source: Referenced from www.sharedata.co.za on 25th February 2014 the top 5 JSE companies, ranked by market capitalisation, accounted for circa 40.5% of the total market capitalisation of the JSE.

The descriptive statistics will determine whether the returns are normally distributed. This will then shape whether a parametric or non-parametric test will be used for further tests of correlation asymmetry. The descriptive statistics computed are the arithmetic mean, standard deviation, skewness and kurtosis. Skewness is used to measure the asymmetry of returns around their means. Negative skewness indicates the data is concentrated more to the left of the mean than to the right. Positive skewness indicates the data is more concentrated to the right of the mean. A normal distribution has a skewness of zero and knowing the skewness of data helps better determine whether future data points are more likely to be more or less than the mean. Kurtosis is used to measure the peak in frequency of returns. Distributions with fat tails will have a kurtosis greater than three and will contain more extreme values than a distribution with a kurtosis of less than three which will have thinner tails and fewer extreme values. A normal distribution will have a kurtosis value of three. The descriptive statistics conclude that the style sub-samples are non-normally distributed therefore a non-parametric test will be used.

3.7 CONCLUSION

The PLR and GARCH-M were both considered as models for measuring conditional correlation. The 10 year data period under investigation considers return exceedances up to and beyond 1.5σ's of either tail. The further standard deviations we move away from the mean, the fewer observations of conditional correlations are captured. There are two reasons for this. Firstly the shares making up the style portfolios are observed to move as much as 1.5σ's (both tails) but this occurs less frequently than for example a 0.5σ move away from the mean – the simple reason is that larger return moves are much rarer than smaller return moves. Secondly as we have imposed the condition on the data to only measure correlation when both the portfolio and the market returns are simultaneously above a pre-specified standard deviation level, the sample is further reduced by this conditioning.

The main test objective is to determine whether the correlation profiles differ at the sub-portfolio level of each chosen style portfolio. The test was run under both frameworks of PLR and GARCH-M. It was discovered that PLR can cope better with smaller samples whilst maintaining integrity and significance of results. For the correlations at the standalone exceedance levels, PLR was thus the more appropriate test for measuring in-sample correlation at individual increments of standard deviation. However, GARCH-M was able to be used over the decade period for the overall correlation of the left versus the right tail. The GARCH-M decade results were thus able to be compared to PLR results for the same period.

The feature of GARCH-M version of the GARCH family models is that it focuses on modelling the heteroskedasticity in the variances of the error terms. It acknowledges that the error term variance is not equal and that it may be reasonably expected that the errors may be larger for some points or ranges than others. As the PLR model is used for the individual exceedance levels and the full left versus right tail comparison against the GARCH-M, it is important to also take into consideration heteroskedasticity for the PLR model. The Stata software package is used to run both models. To control for heteroskedasticity whilst running the PLR model the *Robust* function is used in Stata.

The PLR model can be considered an effective approach to estimating correlation symmetry as it allowed the data to be measured in a conditioned format. The model also takes into consideration daily return points that meet the conditioning criteria, filtered at each exceedance level, and incorporates an indicator variable for daily return data that do not meet the criteria at each exceedance level. Furthermore as there was a high chance the data would suffer from clustering, all data was tested and allocated into either a RE or FE approach method for the best accuracy. Henceforth it was decided the PLR model was the preferred model to be fitted to the sub-samples at each exceedance level.

CHAPTER FOUR

RESULTS AND ANALYSIS

4.1 INTRODUCTION

Chapter one and two have presented the objectives and theoretical background of this study and this chapter applies the analytical framework set out in chapter three to determine whether asymmetry is present in the conditional correlations and to analyse the correlation profiles of the listed style factor sub-portfolios. The chapter will begin by analysing the descriptive statistics (Section 4.2) of the returns of the four style portfolios over the 10 year period with annual rebalancing. Section 4.3 will focus on the diagnostics and comparison of the PLR and GARCH-M models. Section 4.4.1 will test the hypothesis of equal betas at each exceedance level between sub-portfolios as separate, independent tests on negative and positive tails. Table 4-12 in section 4.4.1 will focus on the correlation differentials between sub-portfolios at each exceedance level. The correlation profiles will also be shown and discussed.

4.2 DESCRIPTIVE STATISTICS OF THE STYLE PORTFOLIOS

The arithmetic mean, standard deviation, skewness and kurtosis for the returns of each rebalanced style portfolio from 2003 to 2010 appear in Table 4-1, 4-2, 4-3 and 4-4. All style portfolios and the market use mean returns which are calculated on a daily basis. Table 4-1 represents the style portfolio size with the highest mean return and standard deviation for the Small firm portfolio observed in 2003. During the onset of the 2008 global financial crisis the Large firm portfolio registers its highest standard deviation and lowest mean return. Excessive peakedness is observed in the kurtosis of the small-size portfolio in the years 2004 and 2011 with 9.53 and 13.80 being measured respectively. When taking a closer look at the individual stocks making up the small-size portfolio for those years, it was noted that there were several stocks that increased significantly in value causing the peakedness. These stocks were included as they were above the entry threshold for the thin trading filter.

It is not a surprise that the Small firm portfolio also registers the highest skewness in 2011 of 2.62 which ties in with the high kurtosis of the same year. Over the 10 year period the Small firm portfolio has a higher return than the Large firm portfolio however this is also accompanied by higher standard deviation and kurtosis. Fama and French (1992) find that stock of small companies outperform large companies. The summary statistics mostly reveal this fact, however smaller companies experience slightly more variation – a positive relationship between risk and return for small stocks.

Table 4-1: Descriptive statistics of size style portfolios

Portfolio	Year	Mean (%)	Standard Deviation (%)	Skewness	Kurtosis
SIZE - small	2003	0.4191%	1.0247%	1.1599	3.1368
SIZE - large		0.0861%	0.5563%	0.0521	0.3279
SIZE - small	2004	0.3447%	0.8090%	2.0866	9.5347
SIZE - large		0.1110%	0.4620%	-0.3761	1.8069
SIZE - small	2005	0.3107%	0.6269%	0.6060	0.6683
SIZE - large		0.1329%	0.5062%	-0.3262	0.8780
SIZE - small	2006	0.3339%	0.8972%	0.4984	2.6478
SIZE - large		0.1234%	0.8914%	-1.1297	4.8021
SIZE - small	2007	0.2152%	0.6535%	-0.2028	0.9156
SIZE - large		0.0764%	0.7381%	-0.6866	1.6057
SIZE - small	2008	-0.1363%	0.7680%	0.1951	1.3315
SIZE - large		-0.1348%	1.3111%	-0.4236	1.9870
SIZE - small	2009	0.2076%	0.7429%	0.2305	1.2345
SIZE - large		0.0898%	0.8484%	-0.2997	0.6235
SIZE - small	2010	0.2410%	0.5768%	0.2490	0.3586
SIZE - large		0.0702%	0.6200%	-0.4853	2.5212
SIZE - small	2011	0.2147%	0.8323%	2.6228	13.8040
SIZE - large		-0.0086%	0.6372%	-0.3827	0.9949
SIZE - small	2012	0.1748%	0.5652%	0.3502	0.2627
SIZE - large		0.0583%	0.4196%	-0.4699	0.5338

SIZE STYLE PORTFOLIO (2003-2012)					
SIZE - small	10 years	0.2322%	0.7743%	1.0448	5.3910
SIZE - large	10 years	0.0603%	0.7460%	-0.7820	5.3399

Source: I-Net and author's own estimates.

The PE portfolios, represented in Table 4-2 that are filtered into low and high PE stocks, document the highest mean returns for the Low and High-PE portfolio in the respective years 2004 and 2006. Skewness and kurtosis is the highest in the 2003 portfolio year for High-PE stocks with values of 1.90 and 10.06 respectively. The High-PE portfolio of 2008 has the highest standard deviation and lowest mean return out of all years. This may be attributed to the sudden change in investor appetite towards stocks at the start of the 2008 global financial crisis. Fama and French (1992b) find that High-PE stocks have persistently high earnings relative to book equity that results in high stock prices. On the other hand Low-PE stocks are associated with distress – persistently low earnings relative to book equity that result in low stock prices. During the volatile period of 2008 investors may have perceived a low future earnings environment for some years to come resulting in an overall increase in investor risk aversion towards High-PE stocks. The Low-PE portfolio in 2008 had a higher mean return and lower standard deviation than the High-PE portfolio of the same year. This anomaly may have been attributable to the Fama and French "distress" factor mostly being priced into the Low-PE shares prior to the 2008 financial crisis. Therefore when the 2008 crisis ensued these firms were already at a low PE base and the declines were not as severe as the High-PE shares which had much more room to fall.

Table 4-2: Descriptive statistics of PE style portfolios

Portfolio	Year	Mean (%)	Standard Deviation (%)	Skewness	Kurtosis
PE - low	2003	0.3342%	0.9370%	1.1814	3.2335
PE - high		0.1441%	0.6235%	1.8970	10.0574
PE - low	2004	0.3512%	0.8130%	1.5137	3.9888
PE - high		0.1331%	0.4376%	-0.2973	0.3360
PE - low	2005	0.2793%	0.6114%	0.4821	1.2950
PE - high		0.1494%	0.4899%	-0.0569	1.2534
PE - low	2006	0.3076%	0.9862%	0.2870	3.0737
PE - high		0.1520%	0.7258%	-1.3025	4.8354
PE - low	2007	0.1608%	0.6959%	-0.3655	1.5089
PE - high		0.1325%	0.6412%	-0.8010	1.7206
PE - low	2008	-0.1067%	0.8965%	-0.2183	0.6000
PE - high		-0.1398%	1.0167%	-0.4786	1.7101
PE - low	2009	0.1867%	0.7782%	-0.2731	0.3177
PE - high		0.1168%	0.6777%	0.0683	2.0672
PE - low	2010	0.2002%	0.6013%	-0.0413	0.2909
PE - high		0.0930%	0.5105%	-0.4121	1.9463
PE - low	2011	0.1790%	0.7002%	1.0922	4.1001
PE - high		0.0234%	0.5861%	-0.1591	1.1456
PE - low	2012	0.1431%	0.5367%	0.0989	0.1702
PE - high		0.0739%	0.3484%	-0.1239	-0.0260

PE STYLE PORTFOLIO (2003-2012)					
PE - low	10 years	0.2032%	0.7779%	0.4630	3.2244
PE - high	10 years	0.0876%	0.6354%	-0.5066	4.8724

Source: I-Net and author's own estimates.

Table 4-3: Descriptive statistics of volume style portfolios

Portfolio	Year	Mean (%)	Standard Deviation (%)	Skewness	Kurtosis
VOLUME - LOW	2003	0.4030%	0.9941%	1.4622	3.9849
VOLUME - HIGH		0.1084%	0.6159%	0.0772	0.4126
VOLUME - LOW	2004	0.2868%	0.7127%	1.5000	4.4314
VOLUME - HIGH		0.1492%	0.4966%	-0.2587	0.7504
VOLUME - LOW	2005	0.2860%	0.6135%	0.5134	0.5697
VOLUME - HIGH		0.1639%	0.5378%	-0.5139	1.1194
VOLUME - LOW	2006	0.2614%	0.7742%	0.3559	2.7863
VOLUME - HIGH		0.1943%	0.9632%	-0.6197	4.4600
VOLUME - LOW	2007	0.1944%	0.5612%	-0.4927	1.3062
VOLUME - HIGH		0.1168%	0.8100%	-0.6580	1.2644
VOLUME - LOW	2008	-0.1084%	0.8264%	-0.0620	1.0608
VOLUME - HIGH		-0.1588%	1.2419%	-0.2512	2.0113
VOLUME - LOW	2009	0.1881%	0.6850%	-0.0726	1.0470
VOLUME - HIGH		0.1114%	0.8734%	-0.0665	0.5802
VOLUME - LOW	2010	0.1823%	0.5255%	0.2695	0.7029
VOLUME - HIGH		0.1338%	0.6470%	-0.2665	2.2168
VOLUME - LOW	2011	0.1415%	0.6078%	0.5043	2.4292
VOLUME - HIGH		0.0295%	0.6509%	-0.2727	0.4483
VOLUME - LOW	2012	0.1391%	0.4898%	0.2006	0.3577
VOLUME - HIGH		0.0901%	0.4684%	-0.3565	0.9336

VOLUME STYLE PORTFOLIO (2003-2012)					
VOLUME - LOW	10 years	0.1972%	0.7050%	0.6987	4.1307
VOLUME - HIGH	10 years	0.0936%	0.7704%	-0.5308	4.2374

Source: I-Net and author's own estimates.

The highest mean return and standard deviation in Table 4-3 are registered for the Low-Volume portfolio in 2003. The lowest mean is present in the High-Volume portfolio of 2008, possibly again linked to the start of the global financial crisis. The highest positive skewness observed over the 10 year period is for the Low-Volume portfolio of 2006 with excess skewness and peakedness apparent in the same year (-0.61 and 4.46 respectively). The Low-Volume portfolio included several stocks in 2006 which incurred large rises in price leading to higher comparative figures. Over the 10 year period, the High-Volume portfolio had a lower mean return and higher standard deviation than the Low-Volume portfolio. This is an unusual finding and may relate to a liquidity premium built into the price of more frequently traded stocks.

Table 4-4: Descriptive statistics of dividend yield style portfolios

Portfolio	Year	Mean (%)	Standard Deviation (%)	Skewness	Kurtosis
DY - low	2003	0.3873%	1.0444%	0.9311	1.8792
DY - high		0.1168%	0.4768%	0.4914	2.1719
DY - low	2004	0.2853%	0.7396%	1.3515	3.8646
DY - high		0.1554%	0.3688%	-0.4040	0.5345
DY - low	2005	0.2964%	0.6486%	3.8646	0.6440
DY - high		0.1468%	0.4206%	0.5345	1.0232
DY - low	2006	0.3456%	0.9856%	0.2708	3.1810
DY - high		0.1077%	0.7130%	-1.5017	5.5565
DY - low	2007	0.2427%	0.7835%	-0.6101	1.6591
DY - high		0.0578%	0.5593%	-0.5931	1.8718
DY - low	2008	-0.1419%	1.0200%	-0.2499	0.5240
DY - high		-0.1263%	1.0113%	-0.2766	1.5930
DY - low	2009	0.1764%	0.7723%	-0.1294	0.9282
DY - high		0.1219%	0.7421%	-0.3164	0.8952
DY - low	2010	0.2320%	0.6722%	0.1322	0.6845
DY - high		0.0810%	0.4481%	-0.5340	2.3733
DY - low	2011	0.1437%	0.7213%	0.2489	1.1986
DY - high		0.0159%	0.4801%	-0.5443	1.9607
DY - low	2012	0.1481%	0.5759%	0.3087	0.3309
DY - high		0.0799%	0.3461%	-0.3573	0.1612
DIVIDEND YIELD STYLE PORTFOLIO (2003-2012)					
DY - low	10 years	0.2112%	0.8220%	0.2617	2.6186
DY - high	10 years	0.0755%	0.5947%	-0.7760	4.9320

Source: I-Net and author's own estimates.

Table 4-4 represents the descriptive statistics of portfolios constructed according to dividend yield. The highest mean of returns and standard deviation both occur in the Low-Dividend yield portfolio of 2003. No surprise that the lowest mean is again registered during 2008 for the Low-Dividend portfolio most likely due to investor risk aversion towards low dividend paying stocks with a preference to own higher dividend paying stocks. A reason could be severity of the correction experienced in 2008 which may have led investors to believe that the future earnings environment was going to remain depressed for a lengthy period of time. This could have caused a shift into stocks that had a history of returning cash to investors. This phenomenon may possibly be linked to as far back as Graham and Dodd (1951) who concluded that investors prefer a dollar of dividends to a dollar of capital gain. This relates to the bird in hand theory of dividends. The highest positive skewness is present in the Low-Dividend yield portfolio of 2004 and with a closer look at the stocks included in this portfolio, several of these stocks registered large increases in value leading to peakedness.

4.3 CONDITIONAL CORRELATION MODELS

This section begins by performing diagnostics for the PLR and GARCH-M models and calculates conditional correlation for the left and right tails as complete ranges (instead of measuring correlation at individual exceedance levels). The models are then compared graphically and discussed under section 4.4.2.

4.3.1 PLR tests and diagnostics

The variables J200_neg and J200_pos in Table 4-5 represent the left and right tails of the J200 index on the JSE, respectively. The J200 is comprised of the top 40 tradable shares on the JSE. In the regressions documented in Table 4-5, the J200 is a proxy for the market variable and is also the independent variable. The dependant variables are the returns of the various style portfolios. Using the PLR model the daily return data of the market and style portfolio are regressed under conditions when both variables have moved in the same direction with the same standard deviation away from their respective means.

Each style portfolio is reviewed with the goodness of fit F-test. The F-test tests under a PLR framework whether all the coefficients in the model are different than zero. The p-values of the F-test are all below 5% for each style portfolio. Hence the coefficients are all different from zero and the PLR model is a good fit to the data distribution. The R-squared value is the amount of variance in the dependant variable explained by the independent variables. Overall the PLR model explains a good percentage of the variance of the dependant variable with the highest R-squared being recorded by the Large firm portfolio of 80.93%.

The t-test p-values test the hypothesis that each coefficient is different from zero. The p-values documented are all less than 5% hence the market variables (independent variables) are different from zero and have a significant influence on the style portfolios (dependent variables). The higher the t-value, the higher the relevance of the independent variable. The highest t-value is recorded by the left tail (J200_neg) of the large portfolio and this also happens to have the highest R-squared value of 80.93%.

Sections 4.3.1 and 4.3.2 focus on the broad diagnostics of the both PLR and GARCH-M models with the intention of building up to the comparison of both models (section 4.3.3) so the respective coefficients in Tables 4-5 and 4-6 will only be touched on here. More detail on correlation coefficients will be provided under section 4.4.1 with overall conclusions made in Chapter 5. Nevertheless some of the striking findings will be briefly noted here. Firstly, the left and right tails of each sub-portfolio are asymmetric. In all cases, the left tail of each portfolio has a higher correlation than the right tail and the tails are not symmetric copies of each other. Secondly, there is a distinct difference in correlation between the set comprised of High-DY, High-PE, Large, High-Vol and the set of Low-DY, Low-PE, Small, Low-Vol. The “High” portfolios all exhibit higher correlation for both tails than their “Low” counterparts. Thirdly, the Large firm portfolio has the highest correlation out of all four style portfolios for both the left and right tails – this is not surprising as the J200 is mostly made up of large stocks. The possible theory underpinning these findings will be discussed in sections 4.4.1. and 4.4.2. Overall, the results indicate that the models are a good fit for the data and are reliable.

Table 4-5: Diagnostics of PLR model

	Low-DY portfolio		High-DY portfolio		Low-PE portfolio		High-PE portfolio	
F test p-value	0.0000		0.0000		0.0000		0.0000	
R-squared	0.4945		0.7177		0.5132		0.7341	
Independent variables	J200_neg	J200_pos	J200_neg	J200_pos	J200_neg	J200_pos	J200_neg	J200_pos
Coeffecients	0.3097	0.1187	0.7368	0.4937	0.4156	0.1841	0.7347	0.4912
t-value	8.50	3.61	26.31	18.41	12.18	5.39	27.73	19.43
p-value of t-test	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	Small portfolio		Large portfolio		Low-Vol portfolio		High-Vol portfolio	
F test p-value	0.0000		0.0000		0.0000		0.0000	
R-squared	0.4482		0.8093		0.4773		0.7478	
Independent variables	J200_neg	J200_pos	J200_neg	J200_pos	J200_neg	J200_pos	J200_neg	J200_pos
Coeffecients	0.414	0.1749	0.875	0.6192	0.4731	0.1796	0.8229	0.5838
t-value	11.69	4.80	38.21	28.22	13.37	5.14	33.96	24.64
p-value of t-test	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

4.3.2 GARCH-M tests and diagnostics

The GARCH-M model also has Chi-squared p-values in Table 4-6 which are below zero (Table 4-6) which indicate that the model fits the data well. The p-values of the z-tests show that the majority of coefficients are different from zero except for the Low-PE portfolio. The positive tail of the Low-PE portfolio is the only sub-portfolio where the positive independent market variable does not have a significant influence on the Low-PE portfolio - the p-value is 0.1940.

Overall the tails of the style portfolios under the GARCH-M framework show very similar signs of asymmetry that were also documented under the PLR model. The left tails (J200_neg) across all the portfolios document higher correlation than the right tail (J200_pos) with the market variable. The same “High” versus “Low” effect observed under the PLR model is documented for all the style portfolios under the GARCH-M model.

Table 4-6: Diagnostics of the GARCH-M model[19]

	Low-DY portfolio		High-DY portfolio		Low-PE portfolio		High-PE portfolio	
Chi-squared p-value	0.0000		0.0000		0.0000		0.0000	
Independent variables	J200_neg	J200_pos	J200_neg	J200_pos	J200_neg	J200_pos	J200_neg	J200_pos
Coeffecients	0.3744	0.2001	0.7429	0.5760	0.5369	0.2665	0.7488	0.6462
z-value	14.67	9.94	27.63	20.3	13.75	1.30	30.52	34.19
p-value of z-test	0.0000	0.0000	0.0000	0.0000	0.0000	0.1940	0.0000	0.0000
	Small portfolio		Large portfolio		Low-Vol portfolio		High-Vol portfolio	
Chi-squared p-value	0.0000		0.0000		0.0000		0.0000	
Independent variables	J200_neg	J200_pos	J200_neg	J200_pos	J200_neg	J200_pos	J200_neg	J200_pos
Coeffecients	0.5482	0.2459	0.8360	0.6882	0.5742	0.2858	0.7937	0.6511
z-value	19.25	6.63	38.82	52.73	21.36	8.01	58.90	10.45
p-value of z-test	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

R-squared values are not displayed in Table 4-6 as this measurement is only valid for mean equations, whereas GARCH models deal with variance equations[20]. The best recommended criteria for measuring the model’s goodness of fit is simply by evaluating the significance of coefficients. Overall the coefficients have p-values that are all statistically significant indicating the model is well fitted to the sample.

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[19] Source; I-net and author’s own estimates

[20] Sourced and explained from http://forums.eviews.com/viewtopic.php?f=4&t=1438

4.3.3 Comparison of models

As mentioned previously in the conclusion of Section 3.6 it was noted that PLR can cope better with smaller samples whilst maintaining model integrity and significance of results. For the correlations at individual exceedance levels, PLR was thus the more appropriate test for measuring in-sample correlation at the individual increments of standard deviation.

The GARCH family of models face the reduced sample problem and have trouble approximating and fitting the GARCH framework to a sample of reduced size. To overcome this constraint when running the GARCH-M model this paper measures correlation of the tails as two complete ranges, a left tail (-1.5σ to 0.0σ) and a right tail (0.0σ to +1.5σ), instead of measuring the correlation at each exceedance level range, for example 0.5σ; 1.0 σ and 1.5σ.

The daily return data has to still pass the same test of conditional correlation to be included in the tail range samples. The included portfolio return must simultaneously move in the same direction as the market according to the pre-specified standard deviation ranges of 0-0.5σ; 0.5-1.0σ; 1.0-1.5σ and beyond 1.5σ (the same applies to the left tail). By including all the individual standard deviation range samples into one sample, a separate left and right tail sample, the overall samples increase in size and the GARCH-M model can be fitted to the data. Therefore by considering the 10 year period tails as only two samples there are enough data points to run the GARCH-M model over the decade period. The PLR model is also run over the same decade sample and the correlations are compared over the same period.

The comparison of the correlation profile between the left and right tail of all four style portfolios are fairly similar with respect to their degrees of symmetry. As can been seen by Figure 4.1 through 4.4 asymmetry persists between the left and the right tail under both the GARCH-M and PLR models. Also all sub-portfolios reflect higher correlation with the market on the left tail than the right – no matter which model is used. In addition the “High” versions of all four style portfolio reflect higher correlations across the board, that is, under both tails and both models, than their “Low” version counterparts.

Figure 4-1: Low-DY tail comparison[21]

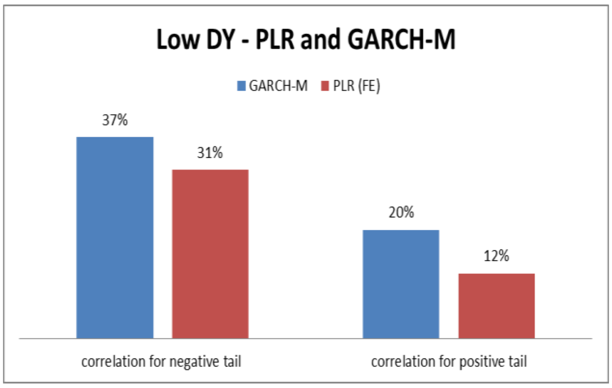


Figure 4-2: High-DY tail comparison[22]

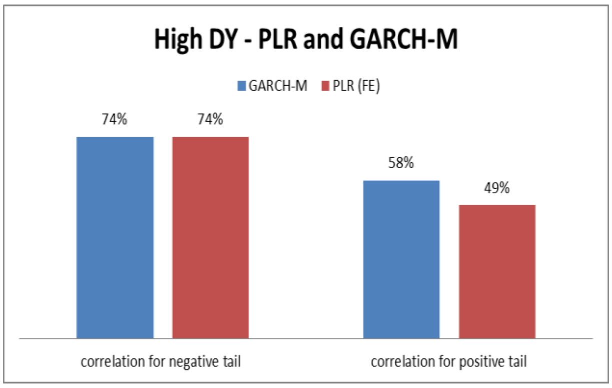


Figure 4-3: Low-PE tail comparison[23]

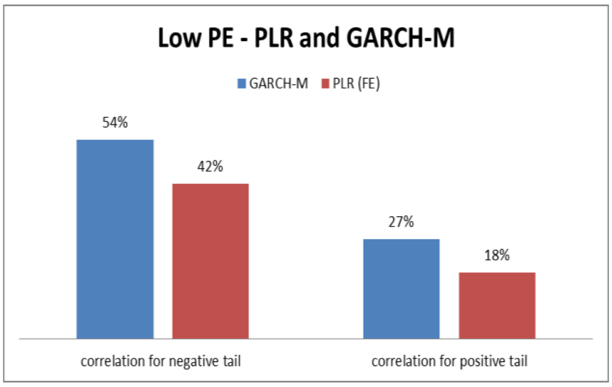


Figure 4-4: High-PE tail comparison[24]

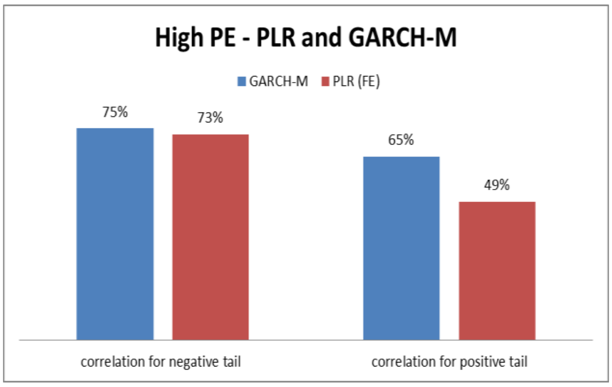


Figure 4-5: Small firm tail comparison[25]

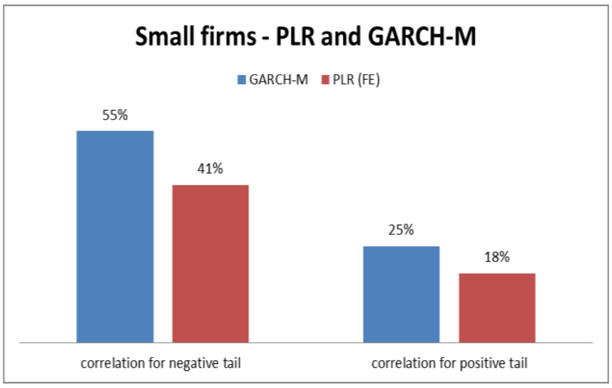
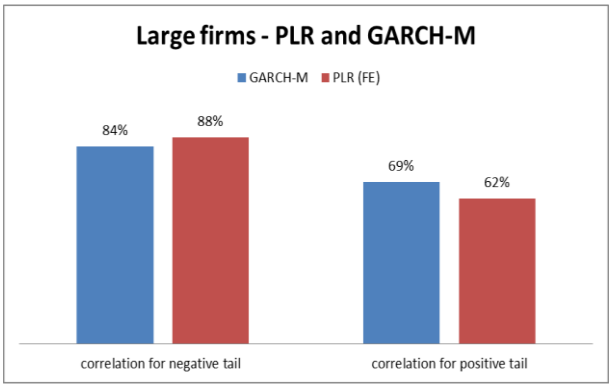


Figure 4-6: Large firm tail comparison[26]



[21] Source; I-net and author's own estimates
[22] Source; I-net and author's own estimates
[23] Source; I-net and author's own estimates
[24] Source; I-net and author's own estimates
[25] Source; I-net and author's own estimates
[26] Source; I-net and author's own estimates

Figure 4-7: Low-Volume tail comparison[27]

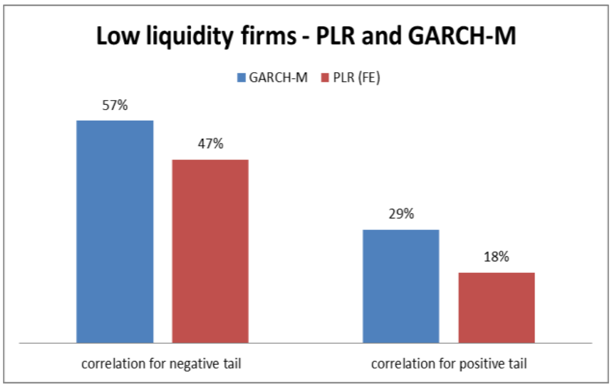


Figure 4-8: High-Volume tail comparison[28]

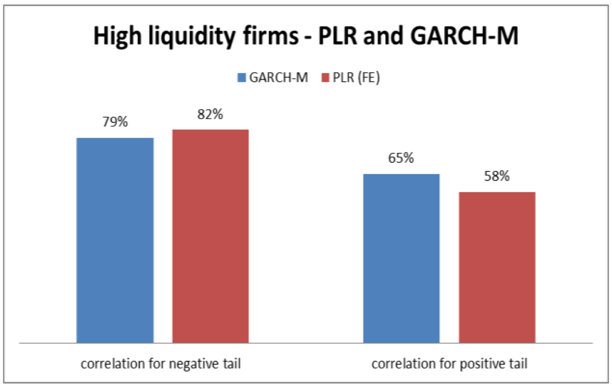


Table 4-7 reflects the difference in correlation for each tail under the PLR and GARCH-M models. The differences when comparing the two models are mild as only 5 out of 16 observations (31% of the time) do the correlations differ by more than 10% with the highest difference only ever being 16%. This is remarkable considering the GARCH-M model is sensitive to reduced data sets. The most important point is the consistency of the asymmetry under both models. The diagnostics observed under section 4.3.1 and 4.3.2 show a common trend across all portfolios where the left tail is more correlated with the market on the downside than the upside. The models track each other closely showing small differences with explicit correlation asymmetry across both frameworks. As PLR can cope better than the GARCH-M model with smaller samples it would be prudent to continue to examine the annual data under the PLR model framework. The various sub-portfolio types are listed in Table 4-7.

Table 4-7: Comparison of correlation across PLR and GARCH-M models[29]

	Correlation for negative tail			Correlation for positive tail		
Type	GARCH-M	PLR	Difference	GARCH-M	PLR	Difference
Low DY	37%	31%	6%	20%	12%	8%
High DY	74%	74%	0%	58%	49%	9%
Low PE	54%	42%	12%	27%	18%	9%
High PE	75%	73%	2%	65%	49%	16%
Small	55%	41%	14%	25%	18%	7%
Large	84%	88%	-4%	69%	62%	7%
Low liquidity	57%	47%	10%	29%	18%	11%
High liquidity	79%	82%	-3%	65%	58%	7%

[27] Source; I-net and author's own estimates
[28] Source; I-net and author's own estimates
[29] Source; I-net and author's own estimates

4.4 CONDITIONAL CORRELATION RESULTS

4.4.1 Piecewise Linear Regression results

In order to test the hypotheses as per section 1.4 one has to first run difference of beta tests across the beta coefficients of each sub-portfolio. The null hypothesis is that the betas are equal and this test allows the sub-portfolio betas to be compared and it can then be determined whether the betas are of differing proportion (null hypothesis rejected). The betas are then compared at each respective exceedance level along the respective tail. This is done via a simple z-test followed by the interpretation of the respective p-values. The results of the z-tests are documented in Tables 4-8 through 4-11. The variable for negative market moves is J200n and for positive moves is J200p. It must be noted that these measurements are only executed when the sub-portfolio and the market are registering simultaneous movements causing them to fall into the same exceedance level.

For illustrative purposes to explain the results we will use the tail region +1.5σ versus -1.5σ taken from Table 4-8 of the PE portfolio tail comparison. The 1.5σ section of Table 4-8 begins with the market variable J200n and compares the betas along the negative tail of the High-PE and Low-PE sub-portfolios at the -1.5σ exceedance level. The z-score is 2.95 with a p-value of 0.0032. A p-value below 0.05 (or 5%) allows the null hypothesis of equal betas to be rejected. With a p-value of 0.0032 it can therefore be concluded that the betas of the PE sub-portfolios differ at the exceedance level -1.5σ. If the betas differ between sub-portfolios at each tested exceedance level it is then implied that the correlation profiles will also differ between sub-portfolios as they will not be copies of each other.

The majority of the beta test results from Tables 4-8 through 4-11 reject the null hypothesis of equal betas at the respective exceedance levels. However at the exceedance level +1.5σ (positive tail) there are two circumstances where very high p-values are recorded (-0.2262 for the PE portfolio and 0.3782 for the size portfolio) hence the null hypothesis of equal betas cannot be rejected. Also at the +1.5σ level, the p-values of the volume and dividend portfolio exceed the 5% level of significance (0.0845 and 0.0751 respectively) resulting in the null hypothesis of equal betas not being rejected. However if the beta comparison for the volume and dividend sub-portfolios are conducted at a 10% level of significance it would result in rejection of the null hypothesis of equal betas. Overall the results at the +1.5σ exceedance level must be treated with caution when comparing tail asymmetry however due to the marginal rejection of the volume and dividend portfolios more weight can be applied to the interpretation of the results at the +1.5σ exceedance level than the PE and dividend sub-portfolios.

Table 4-8: PE portfolio tail comparison[30]

	Hi-PE		**Low-PE**			
market	**beta**	**se**	**beta**	**se**	**z-score**	**p-value**
Tail region +1.5σ versus -1.5σ						
j200n	0.82259	0.11961	0.28619	0.13686	2.95	0.0032
j200p	0.37352	0.12719	0.1376	0.14774	1.21	0.2262
Tail region +1σ versus -1σ						
j200n	0.83947	0.06483	0.44412	0.07691	3.93	0.0001
j200p	0.42567	0.06543	0.10385	0.08231	3.06	0.0022
Tail region +0.5σ versus -0.5σ						
j200n	0.76412	0.03962	0.44984	0.04901	4.99	0.0000
j200p	0.46453	0.03745	0.23418	0.0513	3.63	0.0003
Tail region >0σ versus <0σ						
j200n	0.73471	0.02649	0.41565	0.03413	7.38	0.0000
j200p	0.49129	0.02529	0.18412	0.03416	7.23	0.0000

Table 4-9: Size portfolio tail comparison[31]

	Large-size		**Small-size**			
market	**beta**	**se**	**beta**	**se**	**z-score**	**p-value**
Tail region +1.5σ versus -1.5σ						
j200n	0.93408	0.10347	0.5014	0.15025	2.37	0.0177
j200p	0.51486	0.10027	0.33391	0.17921	0.88	0.3782
Tail region +1σ versus -1σ						
j200n	0.90755	0.05539	0.4934	0.08487	4.09	0.0000
j200p	0.56816	0.05207	0.23135	0.08601	3.35	0.0008
Tail region +0.5σ versus -0.5σ						
j200n	0.88288	0.03449	0.48937	0.05104	6.39	0.0000
j200p	0.57382	0.03218	0.21704	0.05673	5.47	0.0000
Tail region >0σ versus <0σ						
j200n	0.87505	0.02291	0.41399	0.03532	10.95	0.0000
j200p	0.61657	0.02194	0.17597	0.0363	10.39	0.0000

[30] Source; I-net and author's own estimates
[31] Source; I-net and author's own estimates

Table 4-10: Volume portfolio tail comparison[32]

	Hi-Volume		Low-Volume			
market	**beta**	**se**	**beta**	**se**	**z-score**	**p-value**
Tail region +1.5σ versus -1.5σ						
j200n	1.00351	0.07621	0.51079	0.22225	2.10	0.0360
j200p	0.69302	0.0706	0.3627	0.17797	1.73	0.0845
Tail region +1σ versus -1σ						
j200n	0.95468	0.04659	0.41902	0.09567	5.03	0.0000
j200p	0.66382	0.04591	0.29963	0.09893	3.34	0.0008
Tail region +0.5σ versus -0.5σ						
j200n	0.86832	0.03257	0.52531	0.05062	5.70	0.0000
j200p	0.62225	0.03195	0.22987	0.05412	6.24	0.0000
Tail region >0σ versus <0σ						
j200n	0.82299	0.02423	0.47316	0.0354	8.15	0.0000
j200p	0.5838	0.0237	0.17959	0.03497	9.57	0.0000

Table 4-11: Dividend portfolio tail comparison[33]

	Hi-DY		Low-DY			
market	**beta**	**se**	**beta**	**se**	**z-score**	**p-value**
Tail region +1.5σ versus -1.5σ						
j200n	0.72657	0.12758	0.307	0.03622	3.16	0.0016
j200p	0.17218	0.11621	0.2051	0.1922	1.78	0.0751
Tail region +1σ versus -1σ						
j200n	0.76182	0.06614	0.4775	0.0523	3.37	0.0007
j200p	0.393	0.06314	0.2663	0.01009	1.98	0.0475
Tail region +0.5σ versus -0.5σ						
j200n	0.70952	0.04327	0.5035	0.03104	3.87	0.0001
j200p	0.68545	0.01767	0.231	0.07601	5.82	0.0000
Tail region >0σ versus <0σ						
j200n	0.73884	0.02806	0.4587	0.03487	6.26	0.0000
j200p	0.49229	0.0269	0.2043	0.03673	6.33	0.0000

[32] Source; I-net and author's own estimates
[33] Source; I-net and author's own estimates

In Table 4-12 the null hypothesis of symmetry is tested at each exceedance level for the positive and negative tail for portfolios sorted by size, PE, DY and Volume. The rejection of the null hypothesis will imply a difference in the correlation curves of the tested sub-portfolios at the chosen exceedance levels. This will indicate that sub-portfolios (within the same overarching style) react differently for standard deviations moves of equal proportion. Table 4-12 presents the findings for the 10 year period and in addition the differences in empirical correlation are presented at the individual exceedance levels (c = 0.0; 0.5; 1.0; 1.5). The significance of the difference in beta results are documented in Tables 4-8 to 4-11. For the p-values of the symmetry tests, only 4 out of the 64 exceedance levels fail to reject the null hypothesis of symmetry.

Now that it is known at a broad level that there is a difference in betas between sub-portfolios it is important to study the direction of these differences and the impact it may have on the investor. The directional effect can be captured by subtracting one sub-portfolio's correlation at a specific exceedance level from another's, for example in Table 4-12 the difference between the large and small portfolio (Large firm – Small firm) is shown at exceedance levels c_1 through c_4 for each tail separately. The null hypotheses from section 1.4 state that the conditional correlation at an exceedance level for a certain sub-portfolio is equal to the conditional correlation at the same exceedance level for its sub-portfolio counterpart. From Table 4-12 it can be seen that there are differences in conditional correlation at each exceedance level resulting in the majority of the null hypotheses of section 1.4 being rejected. However, as previously mentioned, a few results at the c_4 level must be treated with care as the p-values are above 5% (positive tail: Small Firm; Low-PE; Low-DY; High-DY). The behaviour of correlation profiles at a sub-portfolio level will be discussed under section 4.4.2.

In Table 4-12 as there are four style portfolios (Size, PE, DY and Volume) and four exceedance levels (c_1, c_2, c_3 and c_4) this means there are 16 points along the correlation profile where we can measure a difference in correlation between sub-portfolios. Table 4-12 documents the correlation differences between the correlation exceedance pairs by simply subtracting the correlation between sub-portfolios at a specific standard deviation point. When analysing the positive tail, if the difference in correlation is a positive number, either the Large firm, High-PE, High-DY or the High-Vol (depending which style is being examined) will have a higher correlation than its sub-portfolio counterpart (being Small firm, Low-PE, Low-DY or Low-Vol) at that specific exceedance level. The results show all positive differentials for Large firm, High-PE, High-DY and High-Vol which indicates that these sub-portfolios track the market closer than their sub-portfolio counterparts for market gains. The left hand side of the curve works in a similar manner with a positive correlation differential indicating that the Large firm, High-PE, High-DY or the High-Vol (depending which style is being examined) tracks the market closer for downside moves than their sub-portfolio counterpart. The in-style asymmetry between the positive and negative tails of each sub-portfolio will be discussed separately under sections 4.4.2. This finding concurs with studies on the US stock market by Ang and Chen (2002) and Hong, Tu and Zhou (2007).

Empirically for advances in the market it is noticeable that the sub-portfolios of Large firm, High-PE, High-DY and High-Vol provide a more favourable correlation profile to an investor as they track and participate more in the gains of the broader market than their sub-portfolio counterparts (shown through a positive correlation differential). The opposite applies for market declines as the Small firm, Low-PE, Low-DY and Low-Vol provide a more suitable correlation profile to investors, than their sub-portfolio counterparts, as they track the market less during declines. It must be noted that even though these sub-portfolios track the market less for the negative tail, than their counterparts, they still register higher correlations than their respective positive tails (as noted under section 4.3.2 through Table 4-6).

As mentioned under the EMH section of section 2.2 this study will only focus on the correlation aspect of MPT and will not explore the whole theory of diversification. Nevertheless the crux of MPT is that the hypothetical investor is offered one of two options: the investor can select the highest expected return for any given level of risk, or the lowest level of risk for any given expected return. MPT cannot be fully applied to this study as the correlations are conditioned according to specific exceedance levels whereby the sub-portfolio and the market are simultaneously behaving in a similar manner on the same trading day. This means that the return data, not meeting the conditional criteria, will be excluded from the sample. Nevertheless from a correlation perspective, the set of sub-portfolios Small firm, Low-PE, Low-DY and Low-Vol are less correlated for market declines than their counterparts and the sub-portfolio Large firm, High-PE, High-DY and High-Vol are by in large more correlated than their counterparts for market advances. So the investor can either choose a sub-portfolio that performs well during market advances but tracks the market closely for declines or the other alternative is a sub-portfolio that performs well during market declines but tracks the market less for advances. Maybe a long/short strategy will be the optimal combination, taking the best from each sub-portfolio, but this is a discussion saved for possible future research.

There is an important link between the failure to reject the null hypothesis of equal betas for the positive region of each sub-portfolio – covered under Tables 4-8 to 4-11 (denoted as the variable J200p in these tables) - and certain of the high p-values experienced at level c_4 (1.5σ) in Table 4-12. The failure to reject the null hypothesis of equal betas occurs at the +1.5σ exceedance level and is rejected for all four portfolios (in Tables 4-8 to 4-11). The p-values for the positive tail at c_4 for the Small firm, Low-PE, High-DY and Low-DY are all above the 5% level of significance. It may be that these portfolios contributed to the high p-values experienced in Table 4-12 which compares the correlation profiles between sub-portfolio under the separate positive and negative tail regions. Interestingly, at exceedance level -1.5σ, the p-values for the negative tail are all below 5% and the results can be interpreted with an increased level of certainty than the positive tail results at the +1.5σ exceedance level.

Furthermore, style portfolios comprising stocks from the JSE do not mirror each other for the same standard deviation move either side of the mean and their left tail has no resemblance of the right tail. The implication of asymmetry is that portfolios assembled according to style make portfolio management decisions more complex for large standard deviation moves away from the mean. Portfolios may become increasingly correlated with the market portfolio as exceedance levels are increased to the left tail but then they are mildly correlated for large positive shifts in the market portfolio. In the Hong, Tu and Zhou (2007) study, very few of the null hypotheses are rejected. In this study the majority of the null hypotheses of symmetry are rejected.

Table 4-12: Comparison of correlation profiles[34]

Portfolio	c1 = 0.0	c2 = 0.5	c3 = 1.0	c4 = 1.5
Size-sorted portfolios				
Positive tail (Large firm - Small firm)	44.06%	35.68%	33.68%	18.10%
P-value for Large firm portfolio	0.0000	0.0000	0.0000	0.0000
P-value for Small firm portfolio	0.0000	0.0000	0.0080	0.0690
Negative tail (Large firm - Small firm)	46.11%	39.35%	41.42%	43.27%
P-value for Large firm portfolio	0.0000	0.0000	0.0000	0.0000
P-value for Small firm portfolio	0.0000	0.0000	0.0000	0.0020
PE-sorted portfolios				
Positive tail (High-PE - Low-PE)	30.72%	23.04%	32.18%	23.59%
P-value for High-PE portfolio	0.0000	0.0000	0.0000	0.0040
P-value for Low-PE portfolio	0.0000	0.0000	0.2080	0.3550
Negative tail (High-PE - Low-PE)	31.91%	31.43%	39.54%	53.64%
P-value for High-PE portfolio	0.0000	0.0000	0.0000	0.0000
P-value for Low-PE portfolio	0.0000	0.0000	0.0000	0.0400
DY-sorted portfolios				
Positive tail (High-DY - Low-DY)	28.80%	45.45%	12.67%	-3.29%
P-value for High-DY portfolio	0.0000	0.0000	0.0000	0.1410
P-value for Low-DY portfolio	0.0000	0.0000	0.0030	0.1990
Negative tail (High-DY - Low-DY)	28.01%	20.60%	28.43%	41.96%
P-value for High-DY portfolio	0.0000	0.0000	0.0000	0.0000
P-value for Low-DY portfolio	0.0000	0.0000	0.0000	0.0280
Volume-sorted portfolios				
Positive tail (High-Vol - Low-Vol)	40.42%	39.24%	36.42%	33.03%
P-value for High-Vol portfolio	0.0000	0.0000	0.0000	0.0000
P-value for Low-Vol portfolio	0.0000	0.0000	0.0030	0.0470
Negative tail (High-Vol - Low-Vol)	34.98%	34.30%	53.57%	49.27%
P-value for High-Vol portfolio	0.0000	0.0000	0.0000	0.0000
P-value for Low-Vol portfolio	0.0000	0.0000	0.0000	0.0260

Table 4-13 documents the average of the correlation differentials across the exceedance levels c_1 through c_4. The correlation differentials for the positive and negative tails are ranked largest to smallest. The largest divergence is recorded for both the positive and negative tails of the Volume style portfolio. The smallest divergence is documented for both the positive and negative tails of the DY sub-portfolios. An investor could take advantage of this wide divergence by employing a long/short strategy to the sub-portfolios depending on which side of the tail is being considered.

[34] Source; I-net and author's own estimates

However asset allocation and investment strategy are not the objectives of this paper but may be a worthwhile avenue for future research.

Table 4-13: Average correlation differentials[35]

Style portfolio	Average of c1 to c4
Positive tail (ranked highest to lowest)	
Volume positive tail (High-Vol - Low-Vol)	37.28%
Size positive tail (Large firm - Small firm)	32.88%
PE positive tail (High-PE - Low-PE)	27.38%
DY positive tail (High-DY - Low-DY)	20.90%
Negative tail (ranked highest to lowest)	
Volume negative tail (High-Vol - Low-Vol)	43.03%
Size negative tail (Large firm - Small firm)	42.54%
PE negative tail (High-PE - Low-PE)	39.13%
DY negative tail (High-DY - Low-DY)	29.75%

As the null hypothesis of equal correlation have been rejected and in addition the average divergences between sub-portfolios (Table 4-13) have been documented, it is now important to consider which sub-portfolios track the market the most (for advances) and the least (for declines). Again an average will be employed across the exceedance levels c_1 through c_4. These averages will be calculated from correlation coefficients derived from Tables 4-8 through 4-11 and are documented in Table 4-14.

Table 4-14: Average correlation coefficients[36]

Size sub-portfolio	**SIZE - small**	**SIZE - large**
average for negative tail	47.45%	89.99%
average for positive tail	23.96%	56.84%
PE sub-portfolios	**PE - low**	**PE - high**
average for negative tail	39.89%	79.02%
average for positive tail	16.49%	43.88%
DY sub-portfolios	**DY - low**	**DY - high**
average for negative tail	43.67%	73.42%
average for positive tail	22.67%	43.57%
Volume sub-portfolios	**VOL - low**	**VOL - high**
average for negative tail	48.21%	91.24%
average for positive tail	26.79%	64.07%

[35] Source; I-net and author's own estimates
[36] Source; I-net and author's own estimates

From Table 4-14 it can be noted that the positive tail of the High-Volume portfolio tracks the market the closest at an average of 64.07% for advances in the broader market (followed by the Large firm, High-PE and High-DY sub-portfolios). When considering the negative tail it would be most beneficial to an investor to have a portfolio that is impartial to broader market declines. The lowest recorded average correlation on the downside (negative tail) is 39.89% for the Low-PE portfolio. The Low-PE portfolio is then followed by the Low-DY, Small firm and Low-Volume sub-portfolios.

4.4.2 Correlation profiles

Each conditional correlation finding is displayed graphically in a two dimensional x-y chart. The line charts are plotted according to the correlation (y-axis) documented at each standard deviation increment (x-axis) away from the respective means of both the market and the style portfolio. For the daily returns to be included in the correlation calculation at any specific exceedance level, both the market and respective style portfolio have to register a standard deviation of equal magnitude and direction on the same trading day.

Size portfolios versus the market

Focusing on style portfolios sorted and ranked according to company size the correlation differentials between the Large and Small firm portfolio (Table 4-12) are higher on the left tail than the right tail. Upon closer inspection of Figure 4-9, this phenomenon originates from the fact that the left tail for the Large firm portfolio becomes more correlated with the market as exceedance levels are increased to the left (away from the mean). The left tail for the Small firm portfolio is relatively stable (Figure 4-9) as exceedance levels are increased to the left. Hence with the left tail of the Large firm portfolio becoming more correlated with the market (as exceedances are increased) and the tail of the Small firm portfolio staying relatively flat - the result is an increased correlation differential the further we move away from the mean.

The implications are that a style portfolio made up of large companies will experience more downside market volatility than a small company portfolio. The opposite is found for the positive tail as the correlation differential (Table 4-12) steadily declines as the standard deviation is increased from c_1 outwards to c_4. The reason is that the Large firm portfolio tracks the market less as exceedance are increased, with the Small firm tracking the market more as those same exceedances are increased – the two tails converge towards the tip. This finding has not yet been referenced in literature from comparable international studies.

Figure 4-9: Conditional correlations – Size and market (2003-2012)[37]

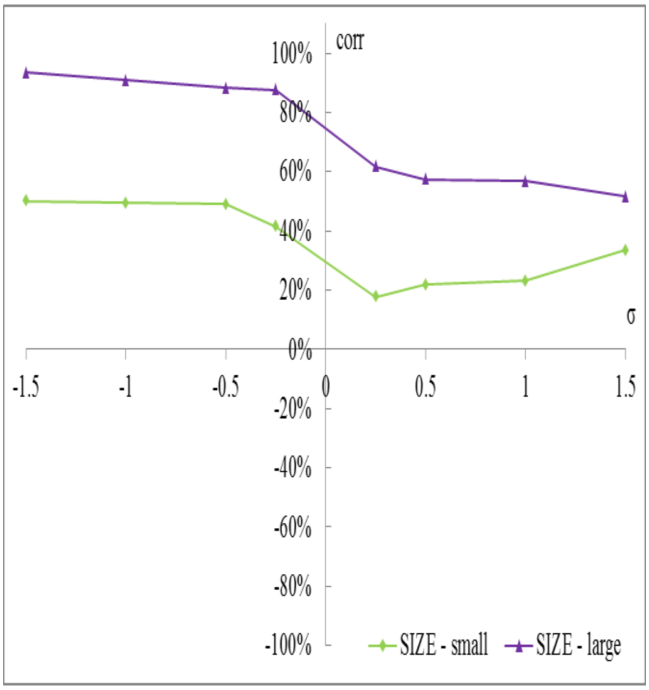


Table 4-15: Conditional correlations – Size and market (2003-2012)[38]

Exceedance levels	SIZE - small	SIZE - large
<(1.5)σ	50.14%	93.41%
<(1)σ	49.34%	90.76%
< (0.5)σ	48.94%	88.29%
<0σ	41.40%	87.51%
>0σ	17.60%	61.66%
>0.5σ	21.70%	57.38%
>1σ	23.13%	56.82%
>1.5σ	33.39%	51.49%

Keim (1983) in a study conducted on the NYSE showed that small firms have higher betas than large firms. Their finding was opposite to that discovered in this JSE study. In support of this study, Lamoureux and Sanger (1989) document on the Nasdaq that smaller firms have lower betas than large firms. This would result in smaller firms moving less than larger firms for equal market moves. This can possibly explain the Small firm portfolio movement compared to the Large firm portfolio. Also van Dijk (2011) argues that the size effect can be the behaviour of less than fully rational investors in the sense that these investors may prefer assets with specific characteristics and that size proxies for the mispricing that their behaviour causes. This could explain the convergence occurring (Figure 4-9) between +1σ to +1.5σ between the Large and Small firm portfolios. Investors may prefer small firms more than large firms during these periods of large advances (observed at greater than +1σ moves for the market).

[37] Source: I-net and author's own estimates.
[38] Source: I-net and author's own estimates.

Now turning the attention to the left tail of Figure 4-9, both portfolios document increasing correlation with the market as exceedance levels are increased from zero to -1.5σ. However this is much milder for the small firm portfolio. The Small firm portfolio is less correlated with the market for the entire stretch of the negative tail. This is noteworthy for the investor as a Small firm portfolio would to a lesser extent resemble the market than a Large firm portfolio during negative shocks. During times of aggressive selling the Small firm portfolio mimics the market to a lesser extent than the Large firm portfolio. A general lack of liquidity in a panicked sell-off could be attributed to this unusual behaviour in small firms. It was documented by van Dijk (2011) that the returns of small firms are possibly sensitive to time-series variation in market liquidity. This concurs with Pastor and Stambaugh (2003) that systematic liquidity variation is a priced source of risk and that the Small firm portfolio already has a liquidity discount priced in hence during market declines the Small firm portfolio will experience lesser declines in value than the Large firm portfolio.

At the face of it a Small firm portfolio provides better diversification during downside moves and resembles the market less than the Large firm portfolio. These findings are in line with Ang and Chen (2002) as the conditional correlation for the Large firm portfolio is greater for downside moves than upside moves. The general trend also supports Longin and Solnik (2001) as the conditional correlation is seen to increase in bear markets but not in bull markets. During a breakaway rally in the broader market (resulting in large standard deviation moves away from the mean) neither the Large nor Small firm portfolio have fully participated in the gain of the broader market. An interesting finding is the increasing correlation experienced within the small size portfolio as it seems to be climbing as the exceedance level increases on the positive tail. This phenomenon may prove to be an interesting topic for future research.

As seen by Figure 4-9, the Large firm portfolio correlation curve follows a unique diagonal shape starting from the top left quadrant and decreasing downwards from left to right. Between the exceedance level range of -1.5σ to 1.5σ the correlation curve shows increasing correlation towards the tip of the left tail and decreasing correlation towards the tip of the right tail. During a heightened period of sporadic risk aversion, investors would have no diversification benefits as large firm shares mimic the market at an increasing rate, the bigger the standard deviation shock, and had increasingly weaker participation in the upside, when the market rallied.

Another noticeable pattern is the overall milder conditional correlations in the Small firm portfolio as opposed to the large firm portfolios. This is clearly noticeable from the Figure 4-9 as the Small firm correlation curves sit below that of the Large firm portfolio. Again this may be attributed to investor preference [see van Dijk (2011)] with a focus on Large firm portfolios with less trading activity taking place in the small firm portfolios.

PE portfolios versus the market

Similarly for portfolios sorted and ranked according to PE ratios, the correlation differential between the High-PE (growth) and Low-PE (value) portfolio is higher along the negative tail than the positive tail (Table 4-12). These findings concur with Hong, Tu and Zhou (2007) as even though their study did not reject symmetry, their p-values indicated that the null hypothesis of symmetry for growth stocks is more likely to be rejected than value stocks. Hence growth stocks are more likely to be asymmetric as seen in Figure 4-10.

Figure 4-10: Conditional correlations – PE and market (2003-2012)[39]

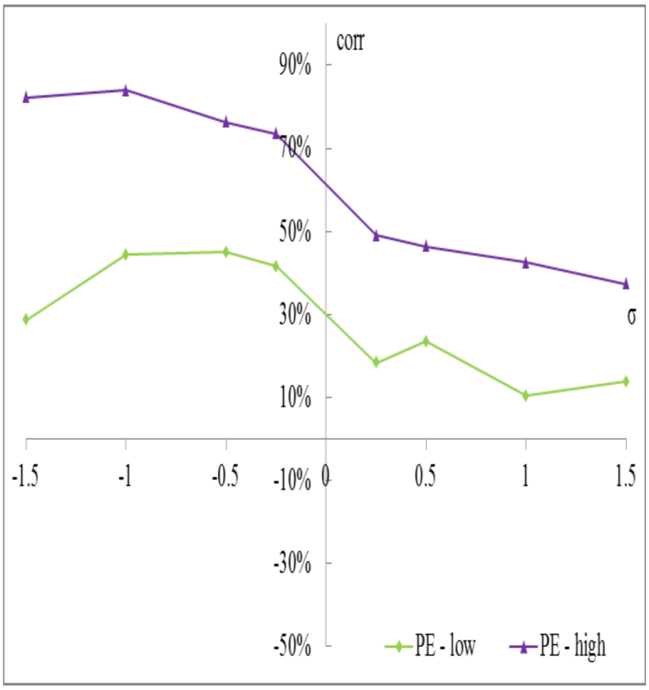


Table 4-16: Conditional correlations – PE and market (2003-2012)[40]

Exceedance levels	PE - low	PE - high
<(1.5)σ	28.62%	82.26%
<(1)σ	44.41%	83.95%
< (0.5)σ	44.98%	76.41%
<0σ	41.56%	73.47%
>0σ	18.41%	49.13%
>0.5σ	23.42%	46.45%
>1σ	10.38%	42.57%
>1.5σ	13.76%	37.35%

[39] Source: I-net and author's own estimates.
[40] Source: I-net and author's own estimates.

The High-PE portfolio shows conditional correlation decreasing as exceedance levels increase to the right of the mean. The Low-PE portfolio shows lower conditional correlation with the market than the High-PE portfolio between zero to the +1.5ϑ exceedance level. The two curves actually converge towards the tips of the tails. Staying with Figure 4-10, to the left of the mean, both Low and High-PE portfolios show a decline in correlation as exceedance levels move outwards towards -1.5σ. Over the 10-year period the Low-PE portfolios are less correlated than their High-PE counterparts on the downside. The Low-PE portfolio has a relatively constant correlation from zero to -1σ then the decline in correlation is significantly noticeable as standard deviations are increased. The High-PE portfolio is also relatively constant beyond -1σ, however it does not abate towards the tail (unlike the Low-PE portfolio).

The findings concur with Longin and Solnik (2001) for High-PE portfolios as the correlation increases in bear markets but not in bull markets. However the correlations for Low-PE portfolios are inconclusive, as there appears to be a significant decline in correlation as we move towards the negative tail, but conversely the Low-PE portfolio plays catch up on the positive tail due to the time lag occurring between +0.5σ to +1σ with correlation increasing slightly towards +1.5σ. It would have been interesting to observe the correlation beyond +1.5σ for Low-PE portfolios but unfortunately there are not enough sample data points beyond +1.5σ to analyse.

The High-PE portfolios in Figure 4-10 has a similar diagonal correlation curve as the Large firm portfolio also representing a negative 'gradient' from left to right. This should be of concern to investors as the high PE portfolio appears to be significantly correlated during sudden declines of the broader market and mildly correlated during sudden up surges in the market. On the other hand the Low-PE portfolio during aggressive selloffs would have resembled very little of the market but would have not participated in strong rallies as well as the High-PE portfolio. Similar to the size analysis, where overall lower correlations were observed in the Small firm portfolio when compared to the Large firm portfolio, the Low-PE portfolio also registers milder (lower) correlations than the High-PE portfolio.

<u>DY portfolios versus the market</u>

At the exceedance level c_4 for the DY style factor (Table 4-12), the p-value results show that there is a failure to reject the null hypotheses of equal correlation at c_4 (1.5σ), hence only the conditional correlation range from c_1 to c_3 can be used to draw any conclusions. On the whole the empirical differences for the positive tails are higher than the negative tail for the first two exceedance points

(c_1 and c_2) with the results switching around at c_3 and the negative tail having a higher correlation differential than the positive tail. At first it seems that the High-DY portfolio is one of the few portfolios that track the market at an increasing rate as exceedance levels are increased on the positive tail, but at c_3 its correlation with the broader market declines to a level of conditional correlation lower than that experienced at c_1.

It is hard to draw a conclusion from the High-DY portfolio with such erratic movements. However taking into consideration the correlation differentials at point c_1, c_2 and c_3, the correlation differentials increase for the negative tail as exceedances are increased and the decrease for the positive tail as exceedances are increased. The reason is that the correlation profiles of the High-DY and Low-DY portfolio diverge towards at the tips of their negative tails and converge towards the tips of the respective positive tails.

Figure 4-11: Conditional correlations – DY and market (2003-2012)[41]

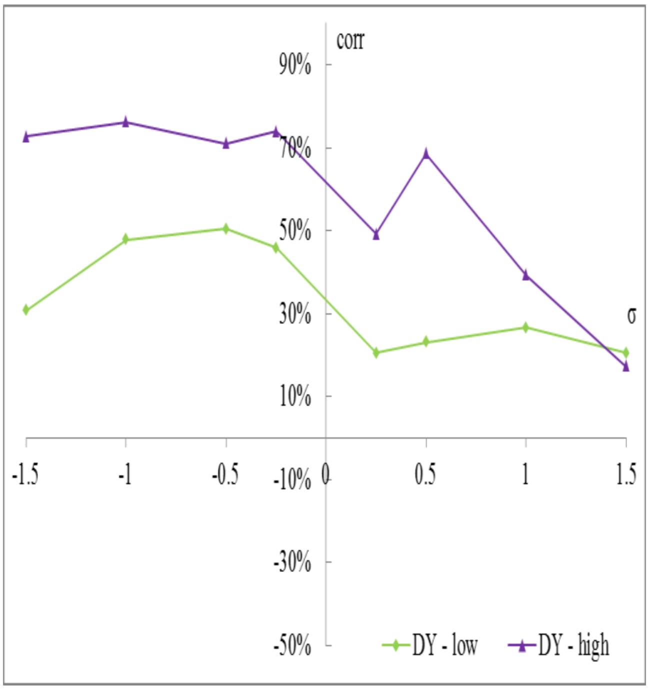


Table 4-17: Conditional correlations – DY and market (2003-2012)[42]

Exceedance levels	DY - low	DY - high
<(1.5)σ	30.70%	72.66%
<(1)σ	47.75%	76.18%
< (0.5)σ	50.35%	70.95%
<0σ	45.87%	73.88%
>0σ	20.43%	49.23%
>0.5σ	23.10%	68.55%
>1σ	26.63%	39.30%
>1.5σ	20.51%	17.22%

Similar to the results for the PE portfolios, the High-DY portfolio (like the High-PE portfolio) declines as the exceedance levels are increased to the right of the mean. The High-DY portfolio crosses over the Low-DY portfolio at +1.5σ and continuing its downward trend (the results at +1.5σ

[41] Source: I-net and author's own estimates.
[42] Source: I-net and author's own estimates.

should be treated with care due to p-values being greater than 5%). A possible reason for this could be investors increasing their exposure to more "riskier" assets by moving further along the risk curve, switching out of high dividend paying stocks into lower dividend paying stocks, with the later perhaps having higher growth prospects. This is noted by Fama and French (2001) that companies that have never paid dividends (or pay very low dividends) are smaller and they seem to be less profitable than dividend payers but they have more investment opportunities with higher asset growth rates. Large moves away from the mean along the positive tail may signal positive investor sentiment towards future growth prospects.These periods could possibly favour companies that have higher asset growth rates (if it is assumed these are resembled by low dividend paying stocks) and interestingly this behaviour is not in line with literature as DY has historically been used as a proxy for value as seen in Kothari and Shanken (1997). This result will be an interesting avenue for future research. .

Along the negative tail, the High-DY portfolio experiences a constant level of conditional correlation in the 70% to 76% range with the market as exceedance levels are increased. The correlation curve of the High-DY portfolio resembles a rough horizontal line. The Low-DY portfolio does exactly the opposite with declining correlation as exceedance levels are increased with correlation of 30.70% at -1.5σ.

The Low-DY portfolios also have milder correlation than the High-DY portfolios across most points with the Low-DY correlation curves tracking below the High-DY curves for most exceedance points with a temporary crossover of the two correlation profiles occurring at +1.5σ. As found for the Large firm and High-PE portfolios the diagonal correlation profile is still intact sloping downwards from the tip of the left tail to the tip of the right tail.

Volume portfolios versus the market

The correlation profile of the High-Volume portfolio has a different shape to the other three style portfolios of Large firm, High-PE and High-DY. All three of these portfolios have a negative gradient correlation curve starting from the top quadrant of the negative tail and then sloping downwards to the furthest point of the positive tail. The difference with the High-Volume portfolio is that the positive tail correlation increases as the exceedance levels are increased. This indicates that the High-Volume portfolio tracks the market more for larger standard deviation moves than smaller standard deviation moves. The correlation differentials for the positive tail do decrease from

c_1 to c_4 but this is not due to a declining correlation profile of the chosen sub-portfolio. Instead both the High-Volume and Low-Volume portfolios actually track the market closer the larger the standard deviation move of the market. The declining differential is caused by the High-Volume portfolio increasing at a slower rate than the Low-Volume portfolio.

The negative tail behaviour is largely the same that was documented for the other three style portfolios with the High-Volume portfolio becoming increasingly correlated with the market as exceedance levels are increased towards the tip of the tail. The Low-Volume exhibits decreasing correlation as exceedance levels are increased. The major implication is that investors in the High-Volume portfolio are taking on more negative tail volatility as standard deviation moves become larger. This switch in volatility can be attributed to the fact that the illiquidity risk premium may have already been priced into the market. This would concur with Pastor and Stambaugh (2001) who argue that stocks with greater illiquidity risk (if priced into the market) decline less than comparative liquid stocks.

Figure 4-12: Conditional correlations – Volume and market (2003-2012)[43]

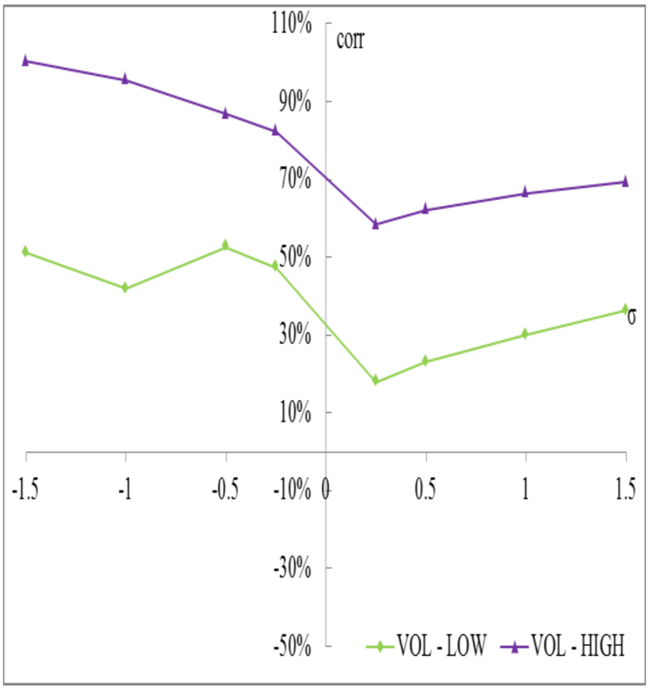


Table 4-18: Conditional correlations – Volume and market (2003-2012)[44]

Exceedance levels	VOL - low	VOL - high
<(1.5)σ	51.08%	100.35%
<(1)σ	41.90%	95.47%
< (0.5)σ	52.53%	86.83%
<0σ	47.32%	82.30%
>0σ	17.96%	58.38%
>0.5σ	22.99%	62.22%
>1σ	29.96%	66.38%
>1.5σ	36.27%	69.30%

[43] Source: I-net and author's own estimates.
[44] Source: I-net and author's own estimates.

The conditional correlations of the High-Volume portfolio follow a "V" shape peaking at the tails. The empirical results for the High-Volume portfolio concur with the findings of Longin and Solnik (2001) and Ang and Chen (2002). Firstly the correlation is generally higher for each exceedance point to the left of the mean, than to the right, therefore supporting the study of Longin and Solnik (2001) which concludes that correlation increases in bear markets, but not to the same extent during bull markets. Similarly the findings of Ang and Chen (2002) are also supported by the High-Volume portfolio which documents correlation to be greater for downside moves than upside moves which is apparent across each exceedance level for the High-Volume portfolio versus the Low-Volume portfolio.

CHAPTER FIVE

CONCLUSION

The objective of the study was to document the conditional correlation between style portfolios and the market portfolio under all conditions. It is imperative to focus on all market conditions but to target each standard deviation point in isolation. Measuring correlation as one globular figure, over a long time period, results in the volatile times being averaged out with the lower volatility periods. The average correlation will appear benign and masks the behaviour of the constructed portfolio under extreme tail events. This can muddy the waters and will mislead investors and asset managers into falsely believing they are holding the right combination of stocks that will be well diversified for large downside moves and perfectly positioned for the upside moves. By uncovering this behaviour at a simple style level will allow further insight into portfolio construction.

Stocks listed on the JSE were sorted according to style attributes and ranked into the portfolio subcategories comprised of the themes: small versus large; growth versus value; high versus low dividend yield and from a trade volume perspective, liquid versus illiquid traded stocks. The daily returns of each standard deviation point were in panel data format and a suitable method to compare standard deviation pairs was the piecewise linear regression model. This technique was able to measure data that was included on a conditioned basis into the correlation calculation and most importantly, allowed the standard deviations to be paired and then compared from either side of their respective means.

The inspiration behind this study came from a finding by Page and Taborsky (2010). During the period January 1970 to February 2008, when both the U.S. and World ex-U.S. stock markets were up more than one standard deviation above their full-sample mean, the correlation between them was -17%. In contrast, when both markets were down more than one standard deviation, the correlation between them was +76%. This international research uncovered evidence of clear asymmetry which this JSE study applied to a style context and the findings uncovered asymmetry in the conditional correlation pairs for all four of the style portfolios. Conditional correlations were measured at the standard deviation increments 0.0, 0.5, 1.0 and 1.5 and the majority of correlation coefficients were significant, except 4 from a total of 64 exceedance levels were above a 5% level of significance. Over the 10-year period, the portfolios were more correlated with the market for extreme down moves than up moves. The implication is that the chosen portfolio begins to resemble the market, the larger the standard deviations moves away from the respective means. Each style portfolio had its own unique signature it terms of asymmetry. The correlation profiles of the positive tail for Large firm, High-PE, High-DY and High-Volume are more favourable than their sub-portfolio counterparts as they track the market closer for advances. For the negative tail the correlation profiles for the Small firm, Low-PE, High-DY and Low-Volume are more favourable than their counterparts as they track the market less for declines.

Ample empirical research has been conducted into the relationship between style factors and the value of the firm, with the symmetric or asymmetric relationship (depending whatever is prevalent) between style factors and the market being largely ignored in the South African context. The objective of studying correlation asymmetry is that it gives one a close up view into the correlation profiles of style portfolios against the market. By observing this behaviour under a wide range of market conditions this knowledge can be effectively used for portfolio design. Conditional correlations between the style portfolio and the market may be asymmetric and visually will display an uneven pattern when correlation profiles are compared either side of the mean. The impact of this asymmetry on portfolio management is that style portfolios may not follow the general movement of the market. This can be a benefit in a down market but conversely can also be a hindrance when the portfolio does not follow the market up during a period of broad gains. These style personality traits can then be used by portfolio managers to construct more robust portfolios which can perform under a wider spectrum of market conditions.

Correlation asymmetry has significant implications for investors as if one had to take the worst case scenario - a portfolio that is strongly correlated with the market for unexpected negative market shocks, resulting in large negative standard deviations away from the mean, and conversely is weakly correlated with the market for sudden jumps in the market due to positive sentiment, the portfolio cannot justify its own existence. Firstly it does not possess any of the benefits of diversification and secondly it is not weighted towards the stocks that are driving the market index up. Faced with this scenario, it would best for the investor to just passively own the market index, as owning a portfolio of this nature, would result in losses and missed opportunities on both sides of the equation.

An investor that prefers to execute a more actively managed strategy may be able to capitalise on the knowledge of correlation profiles. A hedge fund could take simultaneous long and short positions in separate style portfolios. A hypothetical illustration could be a scheduled news event where stock market sensitive data is about to be released – for example the US Federal Reserve's update on the latest taper on bond purchases. Let us assume that a bad news result would be a more than expected decrease in bond purchases, more than what the market anticipated, resulting in a sharp decline in global stock markets. A good news result would be a taper in bond buying in line with economists' expectation. Either way this type of news is reported, it is highly probable the market will shift several standard deviations away from its current mean, in a positive or negative direction. An investor armed with both the knowledge of past correlation profiles of a specific asset class (we will choose PE style portfolios for illustrative purposes to remain with the spirit of this study) and secondly chooses an outcome for the news (based on their own well researched opinion they decide that the US Federal Reserve will reduce bond purchases more than expected – a bad news event) they can position themselves to capitalise on the possible divergence in correlation. Assuming the investor selects the side of the correlation curve that supports their own expectation that the news is negative, they could place a simultaneous long position on the Low-PE portfolio and a short position on the High-PE portfolio. Assuming that the call on the news is correct, this strategy will produce a positive net-return. This is just one, very basic example, which can be used as a trading opportunity. This leads onto an area of possible future research.

Style constructed portfolios are the centre of focus of this study. Future studies can concentrate on other style-driven stock investments. Sector level is just one such example. It will be useful to investigate if certain sectors respond differently to simultaneous shifts in the standard deviation of the market portfolio and the chosen sector portfolio. A portfolio comprised of industrial sector stocks may display a unique correlation profile that differs to financial sector stocks or mining stocks. This future line of study may yield valuable findings.

LIST OF REFERENCES

Abel, A. (1988). Stock prices under time-varying dividend risk: An exact solution in an infinite horizon. *Journal of Monetary Economics, 22*(3), 375-393.

Acharya, V., & Pedersen, L. (2005). Asset pricing with liquidity risk. *Journal of Financial Economics, 77*(2), 375-410.

Aggarwal, R., Hiraki, T., & Rao, R. (1992). Price/Book value ratios and equity returns on the Tokyo Stock Exchange: Empirical evidence of an anomalous regularity. *Financial Review, 27*(4), 589-605.

Amihud, Y., & Mendelson, H. (1980). Dealership market: Market making with inventory. *Journal of Financial Economics, 8*(1), 311-353.

Amihud, Y., & Mendelson, H. (1986). Asset pricing and the bid-ask spread. *Journal of Financial Economics, 17*(2), 223-249.

Amihud, Y., Mendelson, H., & Wood, R. (1990). Liquidity and the 1987 stock market crash. *Journal of Portfolio Management, 16*(3), 65-69.

Ang, A., & Chen, J. (2002). Asymmetric correaltions of equity portfolios. *Journal of Financial Economics, 63*(3), 443-494.

Ang, A., Chen, J., & Xing, Y. (2006). Downside Risk. *Review of Financial Studies, 19*(4), 1191-1239.

Arbel, A., & Strebel, P. (1982). The neglected and small firm effects. *Financial Review, 17*(4), 201-218.

Arbel, A., Carvell, S., & Strebel, P. (1983). Giraffes, institutions, and neglected firms. *Financial Analysts Journal, 39*(3), 57-63.

Arnott, R., & Asness, C. (2003). Surprise! Higher Dividends = Higher Earnings Growth. *Financial Analysts Journal, 59*(1), 70-87.

Auret, C. J., & Sinclaire, R. A. (2006). Book-to-market ratio and returns on the JSE. *Investment Analysts Journal, 63*, 31-38.

Auret, C., & Cline, R. (2011). Do the value, size and January effects exist on the JSE? *Investment Analysts Journal, 74*, 29-37.

Bae, K., & Karolyi, A. (1994). Good news, bad news and international spillovers of stock return volatility between Japan and the US. *Pacific-Basin Finance Journal, 2*(4), 405-438.

Ball, R. (1978). Anomalies in relationships between securities' yields and yield surrogates. *Journal of Financial Economics, 6*(2), 103-126.

Ball, R., & Brown, P. (1968). An empirical evaluation of accounting income numbers. *Journal of Accounting Research*, 159-178.

Ball, R., & Kothari, S. (1989). Nonstationary expected returns: implications for tests of market efficiency and serial correlation in returns. *Journal of Financial Economics, 25*(1), 51-74.

Ball, R., Kothari, S., & Nikolaev, V. (2013). Econometrics of the Basu asymmetric timeliness coefficient and accounting conservatism. *Journal of Accounting Research, 51*(5), 1071-1097.

Banz, R. (1978). *Limited diversification and market equilibrium: An emperical analysis.* Chicago, IL: University of Chicago.

Banz, R. (1981). The relationship between return and market value of common stocks. *Journal of Financial Economics, 9*(1), 3-18.

Banz, R., & Breen, W. (1986). Sample-dependent results using accounting and market data: Some evidence. *The Journal of Finance, 41*(4), 779-793.

Barry, C., & Brown, S. (1984). Differential information and the small firm effect. *Journal of Financial Information, 13*(2), 283-294.

Basu, S. (1977). Investment performance of common stocks in relation to their price-earnings ratios: A test of efficient market hypothesis. *The Journal of Finance, 32*(3), 663-682.

Basu, S. (1983). The relationship between earnings yield market value and return for NYSE common stocks: further evidence. *Journal of Financial Economics, 12*(1), 129-156.
Becker, B., Ivković, Z., & Weisbenner, S. (2011). Local dividend clienteles. *The Journal of Finance, 66*(2), 655-683.
Bekaert, G., & Wu, G. (2000). Asymmetric volatility and risk in equity markets. *Review of Financial Studies, 13*(1), 1-42.
Benartzi, S., Michaely, R., & Thaler, R. (1997). Do changes in dividends signal the future or the past? *The Journal of Finance, 52*(3), 1007-1034.
Berg, A., & Pattillo, C. (1999). Predicting currency crises: The indicators approach and an alternative. *Journal of International Money and Finance, 18*(4), 561-586.
Bertero, E., & Mayer, C. (1990). Structure and performance: Global interdependence of stock markets around the crash of October 1987. *European Economic Review, 34*(6), 1155-1180.
Bhattacharya, S. (1979). Imperfect information, dividend policy and the bird in the hand fallacy. *Bell Journal of Economics and Management Science, 10*, 259-270.
Black, F. (1972). Capital market equilibrium with restricted borrowing. *Journal of Business, 45*, 444-454.
Black, F. (1973). Yes, Virginia, there is hope: Tests of the value line ranking system. *Financial Analysts Journal, 29*(5), 10-14.
Black, F., & Cox, J. (1976). Valuing corporate securities: Some effects of bond indenture provisions. *The Journal of Finance, 31*(2), 351-367.
Black, F., & Scholes, M. (1974). The effects of dividend yield and dividend policy on common stock prices and returns. *Journal of Financial Economics, 1*(1), 1-22.
Black, F., Jensen, M., & Scholes, M. (1972). The capital asset pricing model: Some empirical tests. *in: M. Jensen. ed., Studies In the theory of capital markets*.
Booth, D., & Fama, E. (1992). Diversification and Asset Contributions. *Financial Analysts Journal, 48*(3), 26-32.
Braun, P., Nelson, D., & Sunier, A. (1995). Good news, bad news, volatility and betas. *The Journal of Finance, 50*(5), 1575-1603.
Brenan, M., & Subrahmanyam, A. (1996). Market microstructure and asset pricing: on the compensation for illiquidity in stock returns. *Journal of Financial Economics, 41*(3), 441-464.
Brown, P., Kleidon, A., & Marsh, T. (1983). New evidence on the nature of size-related anomalies in stock prices. *Journal of Financial Economics, 12*(1), 33-56.
Campbell, R., Koedijk, K., & Kofman, P. (2002). Increased correlation in bear markets. *Financial Analysts Journal, 58*(1), 87-94.
Capiello, L., Engle, R. F., & Sheppard, K. (2006). Asymmetric dynamics in the correlations of global equity and bond returns. *Journal of Financial Econometrics, 4*(4), 385-412.
Chalmers, J., & Kadlec, G. (1998). An empirical examination of the amortized spread. *Journal of Financial Economics, 48*(2), 159-188.
Chan, L. K., Hamao, Y., & Lakonishok, J. (1991). Fundamentals and stock returns in Japan. *The Journal of Finance, 46*(5), 1739-1789.
Chang, T., Nieh, C., & Wei, C. (2006). Analysis of long-run benefits from international equity diversification between taiwan and its major european trading partners: an emperical note. *Applied Economics, 38*(19), 2277–2283.
Chen, N., Roll, R., & Ross, S. (1986). Economic forces and the stock market. *Journal of Business, 59*(3), 383-403.
Cho, Y., & Engle, R. (2000). Time-varying betas and asymmetric effects of news: empirical analysis of blue chip stocks. *Unpublished working paper, National Bureau of Economic Research, Cambridge, MA.*

Chordia, T., Sarkar, A., & Subrahmanyam, A. (2005). An emperical analysis of stock and bond market liquidity. *Review of Financial Studies, 18*(1), 85-129.
Choueifaty, Y., & Coignard, Y. (2008). Toward maximum diversification. *The Journal of Portfolio Management, 35*(1), 40-51.
Chowdhury, A. (1994). Stock market interdependencies: evidence from the Asian NIEs. *Journal of Macroeconomics, 16*(4), 629-651.
Chua, D., Kritzman, M., & Page, S. (2009). The myth of diversification. *Journal of Portfolio Management, 36*(1), 236-265.
Conrad, J., Gultekin, M., & Kaul, G. (1991). Asymmetric predictability of conditional variances. *Review of Financial Studies, 4*(4), 597-622.
Datar, V., Naik, N., & Radcliffe, R. (1998). Liquidity and stock returns: An alternative test. *Journal of Financial Markets, 1*(2), 203-219.
De Villiers, J., Lowlings, P., Pettit, A., & Affleck-Graves, J. (1986). An investigation into the small firm effect on the JSE. *South African Journal of Business Management, 17*(4), 191-195.
DeAngelo, H., & DeAngelo, L. (1990). Dividend policy and financial distress: An empirical investigation of troubled NYSE Firms. *The Journal of Finance, 45*(5), 1415–1431.
DeAngelo, H., & DeAngelo, L. (1992). Dividends and losses. *The Journal of Finance, 47*(5), 1837-1863.
Deshmukh, S. (2005). The effect of asymmetric information on dividend policy. *Quarterly Journal of Business and Economics, 44*(1), 107-127.
Easley, D., & O'Hara, M. (1987). Price, trade size and information in securities markets. *Journal of Financial Economics, 19*(1), 69-90.
Easley, D., Kiefer, N., O'Hara, M., & Paperman, J. (1996). Liquidity, information and infrequently traded stocks. *The Journal of Finance, 51*(4), 1405-1436.
Easterbrook, F. (1984). Two agency-cost explanations of dividends. *American Economic Review, 74,* 650-659.
Easterbrook, F. (1984). Two agency-cost explanations of dividends. *The American Economic Review*, 650-659.
Easterday, K., Sen, P., & Stephan, J. (2009). The persistence of the small firm/January effect: Is it consistent with investors' learning and arbitrage efforts? *The Quarterly Review of Economics and Finance, 49*(3), 1172-1193.
Egozcue, M., García, L., Wong, W., & Zitikis, R. (2011). Do investors like to diversify? A study of Markowitz preferences. *European Journal of Operational Research, 215*(1), 188-193.
Eisfeldt, A. (2002). Endogenous liquidity in asset markets. *Unpublished working paper, Northwestern University*.
Eleswarapu, V. (1997). Cost of transacting and expected returns in the NASDAQ market. *The Journal of Finance, 52*(5), 2113-2127.
Ellis, C. (1998). Winning the loser’s game. *McGraw-Hill, New York.*
Elton, E., Grubler, M., Das, S., & Hlavka, M. (1993). Efficiency with costly information: a reinterpreiation of evidence from managed portfolios. *Review of Financial Studies, 6*(1), 1-22.
Fama, E., & Babiak, H. (1968). Dividend policy: An empirical analysis. *Journal of the American Statistical Association, 63*(324), 1132-1161.
Fama, E., & French, K. (1992). The cross-section of expected stock returns. *The Journal of Finance, 47*(2), 427-465.
Fama, E., & French, K. (1992). The cross-section of expected stock returns. *The Journal of Finance, 47*(2), 427-465.
Fama, E., & French, K. (1993). Common risk factors in the returns of stocks and bonds. *Journal of Financial Economics, 33*(1), 3-56.

Fama, E., & French, K. (1995). Size and book-to-market factors in earnings and returns. *The Journal of Finance, 50*(1), 131–155.
Fama, E., & French, K. (2001). Disappearing dividends: changing firm characteristics or lower propensity to pay? *Journal of Financial Economics, 60*(1), 3-43.
Fama, E., & French, K. (2006). The value premium and the CAPM. *The Journal of Finance, 61*(5), 2163-2186.
Fama, E., & French, K. (2012). Size, value, and momentum in international stock returns. *Journal of Financial Economics, 105*(3), 457-472.
Fama, E., & Macbeth, J. (1973). Risk, return, and equilibrium: empirical tests. *The Journal of Political Economy*, 607-636.
Fama, E., Fisher, L., Jensen, M., & Roll, R. (1969). The adjustment of stock prices to new information. *International Economic Review*, 1-21.
Fernholz, R., & Shay, B. (1982). Stochastic Portfolio Theory and. *Journal of Finance, 37*(2), 615-622.
Ferreira, M. A., & Gama, P. M. (2010). Correlation dynamics of global industry portfolio. *Journal of Multinational Financial Management, 20*(1), 35-47.
Fraser, E., & Page, M. (2000). Value and momentum strategies: Evidence from the Johannesburg Stock Exchange. *Investment Analysts Journal, 51*, 14-22.
French, K., Schwert, G., & Stambaugh, R. (1987). Expected stock returns and volatility. *Journal of Financial Economics, 19*(1), 3-29.
Friedman, M., & Savage, L. (1948). The utility analysis of choices involving risk. *Journal of Political Economy, 56*(1), 279–304.
Friend, I., & Blume, M. (1970). Measurement of portfolio performance under uncertainty. *American Economic Review, 60*(4), 607-636.
Gibbons, M., Ross, S., & Shanken, J. (1989). A test of the efficiency of a given portfolio. *Econometrica: Journal of the Econometric Society*, 1121-1152.
Glezakos, M., Merika, A., & Kaligosfiris, H. (2007). Interdependence of major world stock exchanges: How is the Athens Stock Exchange affected? *International Research Journal of Finance and Economics, 7*(1), 24-39.
Glosten, L., & Milgrom, P. (1985). Bid, ask and transaction prices in a specialist market with heterogeneously informed traders. *Journal of Financial Economics, 14*(1), 71-100.
Graham, B., & Dodd, D. (1951). *Security Analysis: Principles and Techniques.* New York: McGraw-Hill Book Company.
Griffin, J. (2002). Are the Fama and French factors global or country specific? *Review of Financial Studies, 15*(3), 783-803.
Grubel, H., & Fadner, K. (1971). The interdependence of international equity markets. *The Journal of Finance, 26*(1), 89-94.
Gulko, L. (2002). Decoupling. *Journal of Portfolio Management, 28*(3), 59-66.
Gwilym, O., Seaton, J., & Thomas, S. (2005). Dividend yield investment strategies, the payout ratio and zero-dividend stocks. *The Journal of Investing, 14*(4), 69-74.
Hamilton, J. (1994). Time series analysis. *Princeton university press, 2*.
Haugen, R., & Baker, N. (1996). Commonality in the determinants of exepcted stock returns. *Journal of Financial Economics, 41*(3), 401-439.
Healy, P., & Palepu, K. (1988). Earnings information conveyed by dividend initiations and omissions. *Journal of Financial Economics, 21*(2), 149-175.
Hicks, J. (1967). Critical essays in monetary theory. *Oxford University Press, Oxford*.
Hoffman, A. (2012). Srock return anomalies: Evidence for the Johannesburg Stock Exchange. *Investment Analysts Journal, 75*, 21-41.
Holmstrom, B., & Tirole, J. (2001). LAPM: A liquidity-based asset pricing model. *The Journal of Finance, 56*(5), 1837-1867.

Hong, Y., Tu, J., & Zhou, G. (2007). Asymmetries in stock returns: statistical tests and economic evaluation. *Review of Financial Studies*, *20*(5), 1547-1581.
Hou, K., Karolyi, G., & Kho, B. (2011). What factors drive global stock returns? *Review of Financial Studies, 24*(8), 2527-2574.
Huberman, G. (2001). Familiarity breeds investment. *Review of Financial Studies, 14*(3), 659-680.
Hwang, Y., Min, H., McDonald, J., Kim, H., & Kim, B. (2010). Using the credit spread as an option-risk factor: Size and value effects in CAPM. *Journal of Banking & Finance, 34*(12), 2995-3009.
Ibbotson, R., Chen, Z., Kim, D., & Hu, W. (2013). Liquidity as an investment style. *Financial Analysts Journal, 69*(3), 30-44.
Ivković, Z., & Weisbenner, S. (2005). Local does as local is: Information content of the geography of individual investors' common stock investments. *The Journal of Finance, 60*(1), 267-306.
Jaffe, J., Keim, D., & Westerfield, R. (1989). Earnings yields, market values, and stock returns. *The Journal of Finance, 44*(1), 135-148.
Janse van Rensburg, S., Friskin, D., & Sharp, G. (2009). A distributional comparison of size-based portfolios on the JSE. *Investment Analysts Journal, 69*.
Jensen, M. (1968). The performance of mutual funds in the period. *Journal of Finance, 23*(2), 389-416.
Jensen, M. (1986). Agency costs of free cash flow, corporate finance and takeovers. *American Economic Review, 76*(2), 323-329.
Jensen, M. (1986). Agency costs of free-cashflow, corporate finance and takeovers. *American Economic Review, 76*, 323-329.
Jiang, X., & Lee, B. (2007). Stock returns, dividend yield and book-to-market ratio. *Journal of Banking & Finance, 31*(2), 455–475.
John, K., & Williams, J. (1985). Dividends, dilution, and taxes: A signalling equilibrium. *The Journal of Finance, 40*(4), 1053-1070.
Jones, C. (1973). Earnings trends and investment selection. *Financial Analysts Journal, 29*(2), 79-83.
Karolyi, G., & Stulz, R. (2003). Are financial assets priced locally or globally? *Handbook of the Economics of Finance, 1*, 975-1020.
Kato, K., & Schallheim, J. (1985). Seasonal and size anomalies in the Japanese stock market. *Journal of Financial and Quantitative Analysis, 20*(2), 243-260.
Keim, D., & Madhavan, A. (1996). The upstairs market for large-block transactions: analysis and measurement of price effects. *Review of Financial Studies, 9*(1), 1-36.
King, M. A., & Wadhwani, S. (1990). Transmission of volatility between stock markets. *Review of Financial Studies, 3*(1), 5-33.
Klein, R. W., & Bawa, V. S. (1977). The effect of limited information and estimation risk on optimal portfolio diversification. *Journal of Financial Economics, 5*(1), 89-111.
Koch, P., & Koch, T. (1991). Evolution in dynamic linkages across daily national stock indexes. *Journal of International Money and Finance, 10*(2), 231-251.
Kothari, S., Shanken, J., & Sloan, R. (1995). Another look at the cross-section of expected returns. *The Journal of Finance, 50*(1), 185-224.
Koutmos, G., & Booth, G. G. (1995). Asymmetric volatility transmission in international stock markets. *Journal of International Money and Finance, 14*(6), 747-762.
Kraus, A., & Stoll, H. (1972). Price impacts of block trading on the New York Stock Exchange. *The Journal of Finance, 27*(3), 569-588.
Kritzman, M., Lowry, K., & Van Royen, A. S. (2002). Risk, regimes, and overconfidence. In S. Figlewski, & R. Levich, *Risk Management: The State of the Art* (Vol. 8, pp. 129-144). Springer US.

Kroner, K. F., & Ng, V. K. (1998). Modelling asymmetric co-movements of asset returns. *Review of Financial Studies, 11*(4), 817-844.
Kyle, A. (1985). Continous auctions and insider trading. *Econometrica, 53*, 1315-1335.
Lakonishok, J., & Shapiro, A. (1986). Systematic risk, total risk and size as determinants of stock market returns. *Journal of Banking & Finance, 10*(1), 115-132.
Lakonishok, J., & Smidt, S. (1984). Volume and turn-of-the-year behavior. *Journal of Financial Economics, 13*(3), 435–455.
Landsman, W., Maydew, E., & Thornock, J. (2012). The information content of annual earnings announcements and mandatory adoption of IFRS. *Journal of Accounting and Economics, 53*(1), 34-54.
Leftwich, R., & Zmijewski, M. (1994). Contemporaneous announcements of dividends and earnings. *Journal of Accounting, Auditing & Finance, 9*(4), 725-762.
Lessard, D. (1973). International portfolio diversification: a multivariate analysis for a group of Latin American countries. *The Journal of Finance, 28*(3), 619-633.
Levy, H., & Sarnat, M. (1970). International diversification of investment portfolios. *The American Economic Review*, 668-675.
Lintner, J. (1956). Distribution of incomes of corporations among dividends, retained earnings, and taxes. *The American Economic Review*, 97-113.
Lintner, J. (1965). The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets. *The Review of Economics and Statistics, 47*(1), 13-37.
Litzenberger, R., & Ramaswamy, K. (1980). Dividends, short selling restrictions, tax-induced investor clienteles and market equilibrium. *The Journal of Finance, 35*(2), 469-482.
Liu, W. (2006). A liquidity-augmented capital asset pricing model. *Journal of Financial Economics, 82*(3), 631-671.
Longin, F., & Solnik, B. (1995). Is the correlation in international equity returns constant: 1960–1990? *Journal of International Money and Finance, 14*(1), 3-26.
Longin, F., & Solnik, B. (2001). Extreme correlation of international equity markets. *The Journal of Finance, 56*(2), 649-676.
Loughran, T. (1997). Book-to-market across firm size, exchange, and seasonality: Is there an effect? *Journal of Financial and Quantitative Analysis, 32*(3), 249-268.
Lustig, H. (2001). The market price of aggregate risk and wealth distribution. *Unpublished working paper. University of Chicago (NBER)*.
Malkiel, B. (2005). Reflections on the efficient market hypothesis: 30 years later. *Financial Review, 40*(1), 1-9.
Markowitz, H. (1952). Portfolio Selection. *The Journal of Finance, 7*(1), 77-91.
McQueen, G., Shields, K., & Thorley, S. (1997). Does the 'Dow-10 Investment Strategy' beat the Dow statiscally and economically? *Financial Analysts Journal, 53*(4), 66-72.
Merton, R. (1980). On estimating the expected return on the market: An exploratory investigation. *Journal of Financial Economics, 8*(4), 323-361.
Miller, M., & Modigliani, F. (1961). Dividend policy, growth, and the valuation of shares. *Journal of Business, 34*(4), 411-433.
Miller, M., & Rock, K. (1985). Dividend policy under asymmetric information. *The Journal of Finance, 40*(4), 1031-1051.
Miller, M., & Scholes, M. (1982). Dividends and taxes: Some empirical evidence. *The Journal of Political Economy*, 1118-1141.
Modigliani, F., & Miller, M. (1958). The cost of capital, corporation finance, and the theory of investment: reply. *The American Economic Review*, 655-669.
Montgomery, D., Peck, E., & Vining, G. (2012). Introduction to linear regression analysis. *John Wiley & Sons, 821*.
Mossin, J. (1966). Equilibrium in a capital asset market. *Econometrica, 35*, 768-783.

Mutooni, R., & Muller, C. (2007). Equity style timing. *Investment Analysts Journal, 65*.
Myers, S. (1984). The capital structure puzzle. *The Journal of Finance, 39*(3), 575-592.
Myers, S., & Majluf, N. (1984). Corporate financing and investment decisions when firms have information the investors do not have. *Journal of Financial Economics, 13*(2), 187-221.
Niederhoffer, V., & Osborne, M. (1966). Market making and reversal on the stock exchange. *Journal of the American Statistical Association, 61*(316), 897-916.
O'Brien, M., Brailsford, T., & Gaunt, C. (2010). Interaction of size, book-to-market and momentum effects in Australia. *Accounting & Finance, 50*(1), 197-219.
Officer, R. (1973). The variability of the market factor of New York Stock Exchange. *Journal of Business*, 434-453.
Page, M. (1996). Further evidence of firm size and earnings anomalies on the Johannesburg Stock Exchange. *De Ratione, 10*(1), 27-44.
Page, M., & Palmer, F. (1993). The relationship between excess returns, firm size and earnings anomalies on the Johannesburg Stock Exchange. *South African Journal of Business Managment, 22*, 63-73.
Page, S., & Taborsky, M. A. (2010). *The myth of diversification: Risk factors vs. asset classes.* Retrieved from PIMCO: http://www.pimco.com/EN/Insights/Pages/TheMythofDiversificationRiskFactorsvsAssetClasses.aspx.
Pastor, L., & Stambaugh, R. (2001). Liquidity risk and expected stock returns. *Working paper, Wharton School, University of Pennsylvania*.
Pastor, L., & Stambaugh, R. (2003). Liquidity risk and expected stock returns. *Journal of Political Economy, 111*(3), 642-685.
Petkova, R. (2006). Do the Fama–French factors proxy for innovations in predictive variables? *The Journal of Finance, 61*(2), 581-612.
Petkova, R., & Zhang, L. (2005). Is value riskier than growth? *Journal of Financial Economics, 78*(1), 187-202.
Plaistowe, T., & Knight, R. F. (1986). Premium to book value may be a contrary indicator. *Investment Analysts Journal, 28*, 35-39.
Rao, R., Aggarwal, R., & Hiraki, T. (1992). Dividend yields and stock returns: Evidence from the Tokyo Stock Exchange. *Journal of Economics and Business, 44*(3), 187-200.
Reinganum, M. (1981). Misspecification of capital asset pricing: Emperical anomalies based on earnings yields and market values. *Journal of Financial Economics, 9*(1), 19-46.
Reinganum, M. (1999). The significance of market capitalisation in portfolio management over time. *Journal of Portfolio Management*, 39-49.
Roll, R. (1977). A critique of the asset pricing theory's tests Part I: on past and potential testability of the theory. *Journal of financial economics, 4*(2), 129-176.
Rosenburg, B., Reid, K., & Lanstein, R. (1985). Persuasive evidence of market inefficiency. *Journal of Portfolio Management, 11*(3), 9-16.
Ross, S. (1976). The arbitrage theory of capital asset pricing. *Journal of economic theory, 13*(3), 341-360.
Rozeff, M. (1982). Growth, beta and agency costs as determinants of dividend payout ratios. *Journal of financial Research, 5*(3), 249-259.
Scholes, M. (1969). A test of the competitive hypothesis: the market for new issues and secondary offerings. *Unpublished PH.D. thesis, Graduate School of Business, University of Chicago*.
Schwert, G. (1989). Why does stock market volatility change over time? *The Journal of Finance, 44*(5), 1115-1153.
Sharpe, W. (1992). Asset allocation: Management style and performance measurement. *Journal of Portfolio Management, 18*(2), 7-19.

Sharpe, W. F. (1964). A theory of market equilibrium under conditions of risk. *The Journal of Finance, 19*(3), 425-442.
Shefrin, H., & Thaler, R. (1988). The behavioral life-cycle hypothesis. *Economic Inquiry, 26*(4), 609-643.
Shiller, R. (2000). Irrational Exuberance. *Princeton, Princeton University Press*.
Solnik, B., Boucrelle, C., & Le Fur, Y. (1996). International market correlation and volatility. *Financial Analysts Journal, 52*(5), 17-34.
Statman, M. (2004). The diversification puzzle. *Financial Analysts Journal, 60*, 44-53.
Strugnell, D., Gilbert, E., & Kruger, R. (2011). Beta, size and value effects on the JSE. *Investment Analysts Journal, 74*, 1-17.
Tobin, J. (1958). Liquidity preference as behavior towards risk. *Review of Economic Studies, 25*(2), 65-86.
Van Rensburg, P., & Robertson, M. (2003a). Style characteristics and the cross-section of the JSE returns. *Investment Analysts Journal, 57*, 7-15.
Van Rensburg, P., & Robertson, M. (2003b). Size, price-to-earnings and beta on the JSE Securities Exchange. *Investment Analysts Journal, 58*, 7-16.
Van Royen, A. (2002). Financial contagion and interntional portfolio flows. *Financial Analysts Journal, 58*(1), 35-49.
Vassalou, M., & Xing, Y. (2004). Default risk in equity returns. *The Journal of Finance, 59*(2), 831–868.
Visscher, S., & Filbeck, G. (2003). Dividend-yield strategies in the Canadian stock market. *Financial Analysts Journal, 59*(1), 99-106.
Visscher, S., & Filbeck, G. (2003). Dividend-yield strategies in the Canadian stock market. *Financial Analysts Journal, 59*(1), 99-106.
Von Furstenberg, G., Jeon, B., Mankiw, N., & Shiller, R. (1989). International stock price movements: links and messages. *Brookings Papers on Economic Activity*, 125-179.
von Neuman, J., & Morgenstern, O. (1944). Theory of games and economic behavior. *Princeton University Press, Princeton, New Jersey*.
Watts, R. (1973). The information content of dividends. *Journal of Business, 46*, 191-211.
Zhang, L. (2005). The value premium. *The Journal of Finance, 60*(1), 67-103.