CAN MARKET STATE AND MARKET VOLATILITY EXPLAIN TIME VARYING MOMENTUM PROFITS IN SOUTH AFRICA?

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Abstract

Strategies based on return continuation have been shown to return a premium unexplained by common risk factors. These strategies are collectively called momentum. Momentum strategies experienced dramatic losses following the volatility episode during the 2008 and 2009 financial crisis. This study therefore tests if volatility and/or market state have any explanatory power for momentum payoff through time.

This is the first study to examine the time-varying nature of momentum payoff in South Africa. Previous studies have focused on cross-sectional tests of momentum. These studies are primarily concerned with the existence of momentum on the JSE, the strength of the anomaly and any interaction with other known anomalies. Conversely, this study tests if momentum payoffs through time change as lagged values of volatility change, where volatility is simply the lagged 12-month market volatility.

The study also examines whether momentum payoff is affected by the state of the market. Market state is defined using the return of the 6-month market return. A positive market state is one where the prior 6-month return has not been negative. The converse will mean that the market is in a negative state.

As a robustness measure, this study considers both equal weighting and value weighted strategies on lookback periods covering 3, 6, 9 and 12 months of prior returns. Furthermore, the study also includes size balanced momentum as well as different window periods for defining volatility and market state.

For the JSE, it would appear that when volatility increases, this is not followed by reduced momentum payoffs. This is true regardless of weighting scheme or lookback period. Furthermore, even when momentum is considered on size balanced portfolios, the results do not change across the board. Consequently, momentum strategies that reverse to a loser minus winner payoff in periods of high volatility do not outperform a standard momentum strategy.

The reasons for the insignificance of volatility are unclear. One potential factor could be the consistent drop in the payoff to momentum. The changes in volatility simply do not follow this

overall trend. In addition, on closer inspection, when lagged volatility increased in 2008, the payoff to momentum did not decrease immediately following this. In fact, the worst return of the period came immediately before lagged volatility started to increase.

These results make momentum in South Africa an even greater mystery than before. The results of this paper are an indication that although momentum has been known to exist in multiple countries, the factors that drive momentum are different in each country. Further research can aid to clarify the momentum anomaly in South Africa, with one potential avenue being momentum and liquidity.

Declaration

I, Mwangele Kaluba, declare that this research paper is my own work and that I have correctly acknowledged the work of others. It is submitted to fulfil the requirements for the degree of Master of Commerce in Business Finance at the University of the Witwatersrand, Johannesburg. I declare that this research paper has not been submitted for any other degree or examination in this or any other institution.

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DEFINITIONS OF TERMS AND ABBREVIATIONS

ALSI: All Share Index

AMEX: American Exchange

APT: Arbitrage Pricing Theory is a multi-factor asset pricing model. This was formulated by Chen, Roll and Ross (1986). The model was developed for the computation of forward-looking asset returns. Employed in the model is a hypothesised linear relationship between returns and macroeconomic factors. Past returns are used to calculate forward looking expected returns.

CAPM: Capital Asset Pricing Model is an asset pricing model that uses market risk as the sole factor that cannot be diversified and therefore the only risk that one should be compensated for. CAPM computes an expected return that is used to price an asset (Sharpe, 1964).

EMH: Efficient Market Hypothesis states that prices fully reflect all available information. Prices only change on arrival of new information to the market. Since new information is unpredictable, price changes are unpredictable (Fama, 1970).

JSE: Johannesburg Stock Exchange

MOMENTUM: A strategy that involves buying past winners and selling past losers, where winners and losers are ranked on returns in the past 12-months or less.

MOMENTUM PAYOFF: The return difference between the winner's portfolio and the loser's portfolio. This is also known as winner minus loser.

NASDAQ: Second largest stock exchange in the United States of America

NBER: Nation Bureau for Economic Research

NYSE: New York Stock Exchange

SARB: South African Reserve Bank

WML: Winner minus Loser

1 INTRODUCTION

This chapter introduces the topic by first giving a brief background on momentum globally and in South Africa. Thereafter, the aim of this research undertaking is provided along with objectives, motivation for the study as well as potential benefits of the study. Lastly, this chapter provides a clear outline of the key hypotheses designed to aid in answering the research question.

1.1 BACKGROUND

There is substantial evidence that both supports and refutes the EMH. There is no short supply of critical evidence against the EMH, chief among which is a strategy based on return continuation called momentum. Momentum investing functions by purchasing the best performing shares within a relatively short time frame and selling shares that have performed the worst in the same time frame. Typically, the lookback period used to measure past performance of shares is no more than a year. The first development of this strategy is considered seminal work in the field of Finance. When momentum was first introduced to the literature by Jegadeesh and Titman (1993), it was a momentous moment for EMH sceptics. The study ranked shares on prior returns and bought the best ten winning shares and sold the worst losing shares. The results showed that this strategy generates significant returns that a risk-based framework cannot explain. Momentum is also significant in many countries, showing that it is a pervasive anomaly and is likely not due to data mining.

In South Africa, the first piece of research to test for momentum was Fraser and Page (2000), who find momentum is not only existent on the JSE but also yields significant returns. The anomaly is later re-examined by Page, Britten and Auret (2013), who find momentum strategies earn significant returns in South Africa. Interestingly, the authors note that the momentum payoff to be lower between January 2002 and December 2010 in comparison to January 1995 and December 2001. This is hypothesised to the financial crisis of 2008 and 2009 but do not investigate it any further. This was a hint at the impact that volatility may have on the payoff to momentum.

In the United States (US), momentum strategies suffered monumental losses during the period of 2008 and 2009. The first few months of 2009 saw some strategies lost as much as 73% (Barroso and Santa-Clara, 2015). These extreme payoffs are a direct motivation for the study by Wang and Xu (2015), which sets out to test if volatility has explanatory power for momentum payoff. As it turns out, volatility is significant in tests of explanatory power. Volatility remains significant even with the inclusion of other variables that other studies prior to Wang and Xu (2015) find to be significant. These variables are the “market state” and “business cycle”. Construction of the former is done with the lagged market return.

1.2 RESEARCH GAP AND OBJECTIVES

1.2.1 Motivation for the study

The results of Wang and Xu (2015) directly motivate this study. The paper finds volatility to be highly significant in momentum profits in the US in the second part of the sample, which included the volatile period of 2008 and 2009. The authors also suggest the use of a refined momentum strategy, where volatility is used to predict reversals to momentum. Following these events, Wang and Xu (2015) implement a reversed momentum strategy with long positions in the losers, with simultaneous short selling of the winner’s portfolio. This refined momentum strategy significantly outperforms the standard momentum strategy. Consequently, this study first tests if volatility is found to be significant in explaining momentum profits through time, followed by if a refined momentum strategy can produce returns over and above the returns to the classical momentum strategy. For Wang and Xu (2015) strategy to be affirmed, the return difference should be positive and significant. This study then serves as an out of sample test of Wang and Xu (2015).

1.2.2 Research objective and question

The objective of this research undertaking is to investigate if volatility has explanatory power for momentum payoff on the JSE. Evidence from the United States has shown that momentum strategies lose profitability when high market volatility is prolonged. In South Africa, the time varying nature of momentum payoff has not had extensive examination. Most of the literature in South Africa focuses on the existence of momentum and whether there is an interaction with any of the known anomalies, value and size being the most examined ones. Page *et al.*, (2013) state briefly that the payoff to momentum between January 2002 and December 2010. This shows that the payoff to momentum changes through time in South Africa.

The latter part of the sample period in the Page *et al.*, (2013) study included the highly volatile 2008-2009 period and the authors suggest that this may have been the cause of the reduction in the payoff to momentum. However, the authors leave it there and do not proceed to explore potential causes for the monotonic reduction in momentum profit through time.

Perhaps the reason why research of time series momentum is scarce in South Africa, is that researchers were more concentrated on ensuring the momentum premium in South Africa is robust. Indeed, the aim of the Page *et al*., (2013) study was to re-examine the momentum anomaly on the JSE to find out if the premium was still significant. Therefore, any time series tests of momentum profits were outside of the scope of the study. Hence, the aim here is to study two potential causes of the reduction in the payoff to momentum through time. To achieve this, the main research question is to be answered is, “Does the state of the market and/or volatility of the market explain time varying momentum profits?”

An imperative point to bear in mind throughout this study is that volatility is not to be associated with idiosyncratic risk. The scope of this study is on systematic risk. Therefore, throughout this study, when volatility is used, it refers to market volatility.

1.2.3 Potential benefits

In addition to volatility, this research tests for market state’s explanatory power as well. This is augmented with business cycle variables as control variables in multivariate regressions. As such, this is the first test for explanatory power on momentum profits in South Africa. This research tests momentum on a time series basis rather than on a cross-sectional basis, which most of the research in South Africa applies. The differences between the two approaches will be discussed in Chapter 2. Lastly, if volatility or market state is found to be significant in explaining momentum profits through time, this study tests if volatility can be used to enhance momentum profits, which can provide useful insights for practitioners. For these reasons, the benefit of this research is the novel addition to South African momentum literature.

1.2.4 Hypothesis testing

Primary Hypothesis

H_0: Volatility and/or market state have no explanatory power for momentum

H_1: Volatility and/or market state have explanatory power for momentum

Secondary Hypothesis

H_0: Volatility and/or market state do not remain significant as an explanatory variable in the presence of other variables

H_1: Volatility and/or remain significant even when control variables are included

For the primary hypothesis, one would reject the null hypothesis if the p-value of the volatility and/or market state variable is significant in a univariate regression of momentum profits on explanatory variables. For the secondary hypothesis, one would reject the null hypothesis if the p-value of the volatility and/or market state variable remains significant with the inclusion of other variables in a multivariate regression on momentum profits. /

1.3 STRUCTURE OF THE STUDY

This research is structured in five chapters and will proceed as follows: **Chapter 2** reviews the literature on momentum in the US and South Africa as well as literature on the effect that volatility and market state have on momentum profits through time respectively. The data used for the research tests conducted for this study along with the variables and methodology are explained in **Chapter 3. Chapter 4** follows on to report the results of the tests described in the preceding chapter. In addition, the chapter will discuss the implication of the results on theory and practice, if any. Lastly, **Chapter 5** is the final chapter, in which the study is concluded.

2 LITERATURE REVIEW

The literature review begins with a discussion of momentums origins, which hails from research in stock markets of developed countries. The chapter that follows goes over the comparatively thin research on momentum in South Africa as well as literature on momentum in emerging markets. The chapter afterwards analyses literature on the explanatory power that macroeconomic variables, market state and volatility have on momentum profits. This sub-chapter on momentum and volatility embarks on a brief discussion of the explanatory power of volatility on momentum profits. Additionally, it details the failure of momentum strategies during periods of high volatility.

2.1 MOMENTUM

Relative strength was the name given to early research that bears a resemblance to price momentum strategies. An infamous case in point is the trading rule discovered by Levy (1967). This trading rule consists of buying a stock if its price is above the 27-week mean. Levy's trading rule generated abnormal positive returns, causing Levy (1967) to proclaim this evidence for the disproval of the EMH. However, as Jenson and Bennington (1970) correctly highlight, such a conclusion was premature because Levy (1967) had set up the rule after testing 68 different trading rules, which was blatant data mining. What was even more egregious was that Levy (1967) had tested the trading rule on the same discovery data and not on out of sample data. Thus, the combination of data snooping and lack of out of sample tests cannot lead one to conclude that the EMH has been refuted. Indeed, Jenson and Bennington (1970) test the trading rule on different data with the results showing that a strategy that simply buys stocks and holds them is superior to the trading rule.

The well-known momentum factor was formalised by the seminal work of Jegadeesh and Titman (1993). This seminal paper assessed strategies where one purchases high performing shares and sells shares with poor performance. The performance of the shares is assessed on returns in the previous 3, 6, 9, and 12 months, which are called the lookback period. Shares are ranked from lowest to highest and at this juncture, the methodology sorts each share into equal portfolios, with 10 shares in each portfolio. The shares with the best performance end up in one portfolio of ten, which is classified as the "winners" portfolio. Similarly, shares with the worst performance wind up in a portfolio of ten, which is designated as the loser's portfolio. Following that, the strategy involves purchasing the winner's portfolio and selling short the loser's portfolio, all at once.

Each lookback period is assigned 3, 6, 9 and 12 months as the holding period for the portfolio, which results in 16 different strategies. The paper repeats the strategies with the difference of skipping the most recent week when evaluating share performance. The reason for skipping a week was to circumvent microstructure effects documented by Lo and MacKinlay (1990). In total, Jegadeesh and Titman (1993) examine 32 portfolios. Calculating returns of the strategies is simple. One simply subtracts the loser's portfolio return from the winner's portfolio return. This is also known as winner minus loser. In this study, it is referred to as momentum payoff.

Of the 32 strategies, 31 produce returns that are positive as well as statistically significant. The paper mostly reports results on the strategy that holds the stocks in the portfolio for 6 months and uses a lookback period of 6 months. This strategy produces a 12.01% annual excess return. The strategy that had the most success was the strategy with a lookback period of 12 months and a holding period of 3 months. However, it does not take longer than two years for the excess returns of all the portfolios to drop by about 50%. This shows that the shares lose momentum over longer horizons, which, according to Jegadeesh and Titman (1993), is indicative of long-term reversal.

The conjecture put forward by Jegadeesh and Titman (1993) is that market participants routinely underreact as well as over-react, which is the source of short-term momentum. The strong results are especially damaging to the EMH put forward by Fama (1970). Achieving excess returns with strategies based on price momentum contradicts weak-form efficiency, in which one cannot use past prices to make abnormal returns (Sewell, 2012).

Fama and French (1993) offers up a long-winded defence of the EMH, in which the authors claim that the size and value anomalies are nothing but an unknown proxy for risk. Therefore, the reason strategies that exploit these anomalies are only profitable because they take on more risk. Consequently, Fama and French (1993) formulate what is now generalised as the "Fama and French three-factor model" by including size and value factors with the market, without a theoretical reason to do so. This is admitted by the authors themselves.

Subsequently, Fama and French (1996) attempt this with momentum, with much less success. Armed with the three-factor model developed in Fama and French (1993), the goal was to assess if the model can explain short to medium term momentum. Adopting Jegadeesh and Titman (1993) methodology, apart from skipping a month rather than a week and only holding for a month, the paper finds evidence of long-term reversal as well as short-term momentum profits. The results show that long-term reversals are consistent with an efficient market even after adjusting with the three-factor model. Disappointingly, for the authors, the model was unsuccessful in explaining momentum. Therefore, abnormal returns of medium-term momentum remain anomalous, inadvertently validating the original claim by Levy (1967).

Indeed Chan, Jegadeesh and Lakonishok (1996) resolve that momentum can only exist because financial markets are inefficient. Specifically, they attribute momentum returns to investors reacting with inadequate speed to information.

Carhart (1997) argues that because momentum is a high turnover approach, transaction costs reduce the return to the strategy. Carhart (1997) claims that this renders momentum impractical for individual stocks. Furthermore, it appears that mutual funds that have high momentum returns do so purely by chance. Mutual funds that do well with momentum have a large weighting in the previous year's winners quite by accident. Mutual funds utilising the strategy underperform net of transaction costs and fees (Carhart, 1997). Additionally, since the three-factor model tested by Fama and French (1996) was unsuccessful, Carhart (1997) appends the model, deciding, for no apparent reason, to throw momentum in as an additional factor.

This factor is created using momentum returns. The model is subsequently tested on momentum payoffs. Unsurprisingly, the three-factor model is bested by the four-factor model, which explains much of the return variation. Carhart (1997) concludes that this is consistent with an efficient market. In the spirit of Fama and French (1993), the paper proclaims that the momentum factor proxies for an unidentified risk. The paper thus presents a rebuttal to assertions that momentum is evidence of market inefficiency. Even so, Carhart (1997) does not attempt to identify the priced risk associated with the momentum factor. In fact, Carhart (1997) remarks that it is up to the reader to interpret what this risk is.

If the EMH holds, the detection of a profitable trading strategy results in the profitability of the strategy tending towards zero, due to overcrowding in the strategy (Lo, 2004). Nonetheless, Jegadeesh and Titman (2001) find evidence to the contrary. The authors update their seminal paper by expanding the universe of stocks expanded to NYSE, NASDAQ and AMEX stocks. Additionally, the paper extends the sample period to 1998. Unlike the Levy (1967) trading rule, momentum continues to perform outside the original sample. In fact, during the nine years after the original sample, momentum achieves higher excess returns. Fama and French (2008) classify momentum as an undisputable anomaly which is remarkably robust.

However, Chordia, Subrahmanyam and Tong (2014) test if the profits of the prominent anomalies such as momentum have continued to be economically significant. The findings demonstrate that the payoffs to these anomalies, including momentum, have experienced a significant decline. There has been a halving of returns to portfolios that follow strategies designed to exploit the well-known anomalies. Furthermore, the results show that the payoff to the momentum have become insignificant.

Chordia *et al*., (2014) state that the shear amount of hedge funds employing strategies to exploit anomalies has led to the reduction in the profitability of said anomalies. Chordia *et al*., (2014) further attribute the reduction in momentum profitability to increased market liquidity, which has reduced the limits to arbitrage that previously kept strategies based on anomalies profitable. Chordia *et al*., note that since the tick size changed from $0.0625 to $0.01 in 2001, trading costs have deteriorated substantially. The reduction in transaction costs has facilitated arbitrageurs to correct mispricing's, which has led to declining profits from anomaly strategies like momentum. This, therefore, can be taken as support of the EMH, that large liquid capital markets will compete away arbitrage opportunities. The result being that market prices will be less predictable, reducing opportunities for profiting from published strategies.

Avramov, Cheng and Hameed (2016) set out to test the claims made by Chordia *et al*., (2014) in order to ascertain if arbitrage has indeed improved, causing a decline in momentum. This is achieved by testing the relationship between changes in liquidity through time and momentum profits. Since momentum is an anomaly that is unexplained by the rational risk factors, limits to arbitrage prevent momentum from ceasing to exist. Therefore, a test of momentum and liquidity is also a test of the relationship between liquidity and the effectiveness of arbitrage. The period under consideration in Avramov *et al*., (2016) is from 1928-2011.

Given the results of Chordia *et al*., (2014), one would expect the relationship between momentum payoffs and market illiquidity to be positive. That is, when markets are illiquid, momentum payoffs should be larger and when markets are liquid, momentum profits should be smaller. Remarkably, Avramov *et al*., (2016) results indicate the opposite. Using a measure of illiquidity lifted from Amihud (2002), the regressions reveal that when market liquidity increases, the payoff to momentum also increases. In the same manner, when market liquidity reduces, the payoff to momentum reduce as well. The results show that a reduction of 0.87% per month in the payoff to momentum when standard deviation is incremented by one (Avramov *et al*., 2016).

With regards to the robustness of the results, Avramov *et al*., (2016) find that the relationship holds true even with large capitalisation shares, which generally tend to have more liquidity than small stocks. In addition, Avramov *et al*., (2016) also test if the results are robust by controlling for momentum payoffs in positive and negative market states. The results still reflect a positive and significant relationship between market illiquidity and momentum payoff.

Contrary to Chordia *et al*., (2014), momentum payoffs are significant when market states are factored into the momentum strategy. This is especially the case when market liquidity is high.

Even with an alternate liquidity risk measure, formulated by Corwin and Schultz (2012), is employed, the significant positive association that momentum payoff has with illiquid market does not dissipate. The payoff to momentum in liquid markets is 1.09, while the payoff to momentum in illiquid markets is -0.69 (Avramov *et al*., 2016).

Since the evidence is robust, this presents a counterintuitive result to the position espoused by Chordia *et al*., (2014). Avramov *et al*., (2016) put forward that illiquid stock markets are a proxy for the real economy, a position also shared by Næs, Skjeltorp and Ødegaard (2011). If the illiquidity of the market proxies for the real economy, this means that the payoff to momentum strategies through time are affected by changes in the economic cycle, an implication favouring the results of Chordia and Shivakumar (2002).

Outside of the US, Rouwenhorst (1998) was the first to test if momentum exists on an international basis. Specifically, the paper tests if momentum strategies are profitable for individual shares on stock exchanges across 12 different European territories between 1978 and 1995. This was performed to confirm momentum as only a US phenomenon discovered by chance or demonstrate it a legitimate anomaly that manifests across multiple stock exchanges in different countries.

The study replicates the methodology of Jegadeesh and Titman (1993), using 3, 6, 9 and 12 as lookback time frames when sorting stocks into portfolios, as well as holding periods with both overlapping and non-overlapping portfolios. The paper finds that the winner minus loser portfolio attains excess returns of around 1 percent per month. This is prevalent throughout the entire sample of stock markets. Similar to US research, the outperformance only lasts about a year. Much like the research in the US, the study cannot attribute these returns to any common risk factor.

Rouwenhorst (1998) also found that momentum and size have a negative association. Moreover, profits reduced in a monotonic fashion when shifting from small capitalisation momentum portfolios to large capitalisation momentum portfolios. Rouwenhorst also tested the link between US momentum and European momentum. From 1980 to 1995, the correlation between US momentum and European momentum was 0.43.

There have since been more studies done in developed markets outside of the US. For instance, Doukas and McKnight (2005) find that between 1988 and 2001, momentum is prevalent and existent on 13 European stock markets. More recently, the findings of Rouwenhorst (1998) remain undisputed after Fama and French (2012) investigate momentum and value in America, continental Europe, UK, Japan and Asia Pacific. Momentum payoff is significant throughout the developed markets under examination, minus Japan (Fama & French, 2012).

Furthermore, momentum decreases steadily when one goes from a momentum portfolio formed on small capitalisation stocks to momentum formed on large capitalisation stocks (Fama & French, 2012). Further evidence on momentum in international markets is presented in Assness, Moskowitz and Pedersen (2013), which demonstrates that momentum is existent and significant across eight different markets and asset classes.

Momentum is also prevalent in emerging markets. Griffin, Ji and Martin (2005) show significant momentum payoffs in 40 territories globally, with Africa, the Americas (barring the US), Europe and Asia included in the study. This sample covers almost all the emerging markets that are on investors radar. For the emerging markets, Africa has a momentum payoff of 1.63, the Americas have a momentum payoff of 0.78 per month and momentum payoff is 0.32 per month in Asia.

The momentum payoff is the lowest in Asian markets, which is still true in spite of the exclusion of Japan, the perennial rebel on momentum. Furthermore, the payoff to momentum in Asia is not significant. However, at country level, 10 countries in Asia, out of 14, have positive momentum payoffs. For the rest of the emerging markets, two of the two African countries in the sample experience positive momentum profits, as well as five out of six countries in the Americas. Since the publication of this paper, Fama and French (2012) have shown momentum to be significant in emerging markets. In addition, Cakici, Fobozzi and Tan (2013) find momentum is still prominent in emerging markets.

More recent findings show that momentum profits have reduced substantially from prior research (Abourachid, Kubo, & Orbach, 2017). Abourachid *et al*., (2017) uses the same methodology to create momentum portfolios as Jeegadesh and Titman (1993), so it stands to reason that the paper has the same portfolio names as Jeegadesh and Titman. The portfolio with stocks formed on a lookback of six months, where the most recent month is ignored, and held for six months yields 1.12% from 1980 to 1995 (Rouwenhorst, 1998). In contrast, Abourachid *et al*., (2017) show that the return to this same strategy has dropped to 0.58%. The paper examines momentum in 10 European countries from 2004 to 2015 using two 6-year sub-periods. The findings indicate that momentum is insignificant in the second half of the sample 2007-2012, across all 10 countries. Abourachid *et al*., (2017), attribute this to the financial crisis episode in 2008 and 2009. Lastly, Abourachid *et al*., (2017), like Fama and French (2012) find that momentum is lower among large stocks than small stocks.

2.2 MOMENTUM IN SOUTH AFRICA

In contrast to US and international literature, research on momentum in South Africa is remarkably thin. The first paper in South Africa to examine was Fraser and Page (2000). The paper attempted to replicate Asness (1997), which demonstrated that value and momentum are negatively related. That is, momentum works best on low value stocks and value works best on loser momentum stocks. Fraser and Page (2000) examined industrial shares from January 1973 to October 1997. The methodology employed in the paper is a mild departure from international literature, with no explanation provided by the authors. The paper does not skip a week to avoid bid-ask bounce, nor does it use cumulative returns. Fraser and Page (2000) find significant and positive momentum return premium in South Africa, with monthly mean returns of 0.39% and -1.83% for winners and losers respectively. Unlike Asness (1997), the study finds that momentum is not dependent on value and neither is value dependent on momentum (Fraser & Page, 2000).

A foundational study for financial research on style factors in South Africa by Van Rensburg (2001) examined various style factors, including momentum, on industrial shares on the JSE. The paper finds that purchasing stocks on the JSE (from the industrial sector) based on historical returns obtains positive abnormal returns. This is used this as a foundation in a re-examination of momentum by Van Rensburg and Robertson (2003), with the results showing a persistence of price momentum. An international study by Griffin *et al*., (2005) that includes South Africa in its sample of 40 countries finds that there is price momentum as well as earnings momentum in South Africa.

Venter (2009) applied the portfolio ranking and formation methodology of Jegadeesh and Titman (1993) to check for momentum on intraday data. The data was only from 2007 but this was still a relatively large sample as the study used short time intervals of 0.5 to 2.5 hours for ranking stocks and 1 to 5 hours for holding stocks. The paper finds that momentum payoff is not statistically different from zero. Therefore, there is no evidence of intraday momentum on the JSE. In fact, the paper finds that winners consistently deliver negative returns while losers deliver positive returns. The conclusion is that Jegadeesh and Titman (1993) portfolio ranking and formation methodology is not appropriate for intraday data.

Page *et al*., (2013) resuscitate South African literature on momentum to uncover profitability of South African momentum in South Africa. Time frame under review is from January 1995 to December 2010, broken up into two parts; January 1995 to December 2001 and January 2002 to December 2010. Momentum construction methodology is almost the same as Jegadeesh and Titman (1993). Bearing in mind that volume biases results towards large capitalisation stocks, turnover therefore proxies for liquidity. Ultimately, the results show that momentum strategies in South Africa produce significant returns in all the years in the sample as well as throughout the total period. The study findings reveal positive and significant returns to momentum trading in the whole sample. The portfolio with a lookback period of six months, held for nine months, achieved the best performance, averaging 2.12% per month.

Owing to the fact the JSE is characterised by low levels of liquidity on over two-thirds of shares listed on the exchange, Page *et al*. (2013) further investigated if liquidity affects the returns of South African momentum. The authors perform a bivariate sort on momentum and liquidity to rank stocks and form portfolios. As it turns out, the impact of illiquid shares on momentum profits is significant. The correlation between momentum and liquidity is negative. High and medium liquidity portfolios attained returns that were greater in magnitude in comparison to the low liquidity momentum portfolio. Thus, the paper was unique as it was the first successfully link momentum to another factor in South Africa. This is true considering Fraser and Page (2000) find that momentum and value are independent.

Page and Auret (2017) set out to confirm the if the momentum anomaly is a prominent and consistent feature of the South African market. The paper uses variations of the classical momentum construction pioneered by Jegadeesh and Titman (1993). However, much of the original construction remains unchanged, such as the lookback periods and holding periods. By contrast, Page and Auret (2017) ignore the most recent month when evaluating share performance, whereas Jegadeesh and Titman only skip a week. Page and Auret (2017) also form portfolios where the most recent month is not excluded when shares are being ranked on past performance. This captures the effect that microstructure concerns on the JSE would have on momentum profits. Additionally, the paper formed five portfolios using a value weighted schema as well as an equally weighted schema. There were thus four combinations which resulted from the two weighting approaches with and without a month being skipped. The paper also applies liquidity and price filters in the sorts. The motivation for this was to find the optimal methodology of momentum portfolio formation for both academic research and investment practice.

Across all the methodology permutations, momentum is highly significant in South Africa for the full sample period (Page & Auret, 2017). The portfolio that achieved the highest return was the rank on six months and "hold" for six months portfolio. Page and Auret (2017) show all portfolios following an equally weighted schema attaining larger returns over their value weighted counterparts. Firstly, Lee and Swaminathan (2000) provide evidence that there is a link between higher liquidity and quicker reversals. Since value weighting increases weights on stocks with large market capitalisations, value weighting increases the liquidity of the portfolio. The liquidity increases because large capitalisation stocks tend to have more liquidity. The second reason could be that equal weighting increases weights on small capitalisation stocks which leads to an interaction with the small capitalisation effect. However, the authors note that this is unlikely to be the case considering Page, Britten and Auret (2016) show the size effect to have mostly died out in South Africa. Thus, according to Page and Auret (2017), there is a chance that the premium in equal weighting is due a low beta or volatility anomaly.

As per results from the US, ignoring the most recent month when sorting shares into momentum portfolios affects payoffs of all momentum constructions, with this effect being statistically significant. All portfolios with both equal weighting and value weighting benefit from skipping a month. This shows that microstructure effects on the JSE do affect the returns to momentum. Furthermore, trading costs reduce the profits to momentum considerably. The paper deduces that the persistence of the momentum anomaly could be due to the limits of arbitrage, where high transaction costs limit the potential for arbitrageurs to exploit the mispricing (Page & Auret, 2017).

Page and Auret (2018) attempt to attribute momentum payoff to risk-based return generating factors. The paper uses three market models for return attribution, namely CAPM advanced by Sharpe (1964) and Litner (1965), Fama and French (1993) three factor model and the Van Rensburg (2002) multifactor model. Much like Fama and French (1996), Carhart (1997) and other international literature, the study demonstrates that momentum profits are statistically significant using all three models. The implication of this is that popular risk factors identified in the literature cannot explain the returns to momentum investing. Therefore, the paper concludes that a risk-based regime cannot explain momentum.

Literature on time variation of momentum payoff in South Africa is virtually none-existent. The vast majority of momentum studies in South Africa utilise a cross-sectional approach. This means that studies either test if momentum is significant on the JSE (Page *et al*., 2013), or for an interaction that momentum may have with other anomalies, like for instance size and value (Page *et al*., 2016), or comparison between different constructions of momentum portfolios (Page *et al*., 2013). By comparison, US literature has several papers that test why momentum payoffs change through time and if the changes are predictable. A few of the papers are discussed at length in the next chapter, but a recent study of note is Avramov *et al*., (2016), with a rather unexpected result. The key revelation from Avramov *et al*., (2016) being that momentum payoffs are larger when markets are highly liquid. Research of this type has yet to be attempted in South Africa.

2.3 EXPLANATORY VARIABLES OF MOMENTUM PROFITS THROUGH TIME

It is worth noting at this juncture the differences between a cross sectional approach and a time series approach to tests of momentum. Cross-sectional momentum studies focus on if and why momentum exists. Furthermore, such studies provide reasons, usually behavioural, as to why momentum exists. Exceptions to this are Fama and French (1996) and Cahart (1997), with the former a failed attempt at explaining the difference in the returns across winner and loser stocks is due to the priced risk factors (beta, size, and value) and the latter doing the same but with momentum factor as an assumed priced risk. On the other hand, time series tests of momentum examine when momentum profits are significant and why this is the case. Tests for time variation in momentum tend to explain that the behavioural explanations that are said to cause momentum are themselves susceptible to change, which in turn affects momentum profits through time.

For example, Jegadeesh and Titman (1993) discover momentum, in the process showing the return premium to be highly significant. Subsequent studies attempt to explain why there is such a huge contrast in performance between the winner and loser portfolios with either a behavioural model or a risk-based explanation. Jegadeesh and Titman (2001) confirm momentum yields significant returns after discovery. However, there is no test to see if the profitability changes every year since the discovery of momentum and why this may be the case. Conversely, according to Avramov, *et al*., (2016), momentum payoffs vary through time based on liquidity of the market. This is distinct from the Page *et al*., (2013) study, in which shares with higher liquidity achieve higher returns.

In South Africa, the only notable mention of time variation in momentum payoff is by Page *et al*., (2013), who notice that momentum payoff is lower from January 2002 to December 2010. Testing why this is the case was outside of the scope of the study, but a brief association with the 2008/2009 volatility episode is made. This is hinting at market states and volatility's potential influence on the payoff of momentum, which is the main undertaking of this research. This chapter reviews literature on momentum and its relationship with the main explanatory variables used in the paper.

2.3.1 Momentum and Macroeconomic Factors

Realistically, momentum does not have a convincing explanation that is rooted in the EMH panacea of extra risk explains any apparent abnormal returns. A few attempts have been made to link momentum with risk. One interesting claim is that in an efficient market, where share returns are modelled by random walk, a shares average historical return is individual is expected to continue in the future and this therefore explains momentum (Conrad & Kaul, 1998). Berk, Green and Naik (1999) offer a similar position with their simulations, based on a rational expectations framework, showing significant medium term return continuation.

Chordia and Shivakumar (2002) investigate common risk factors as the potential cause of momentum. The study is motivated by a lack of sufficient risk-based explanations of momentum, as the explicit consensus is that momentum is behavioural, especially in light of Fama and French (1996) failure to attribute momentum to a meaningful risk factor. Specifically, the risk factors in question are macroeconomic factors. The paper makes use of an expected return model that incorporates lagged macroeconomic variables model to approximate expected returns. The variables include the value weighted market index dividend yield along with the spread between the ten-year Treasury note and the three-month Treasury bill. Additionally, the model includes the yield on the three-month T-bill and the credit default spread. The default spread is the difference between the yield on AAA rated bonds and BBB and below rated bonds. The data utilised has a sample length of 60 months. Running the model results in a one-step-ahead conditional forecast, which is the forecasted returns in the current month. After this, they compare the expected return to momentum returns to determine if the abnormal momentum returns are statistically significant. The paper finds that the model explains a substantial portion of momentum returns.

Chordia and Shivakumar (2002) further delve into the profitability of momentum strategies during economic cycle variations. Employing NBER data, the results show that momentum varies with the business cycle. Specifically, momentum performs better during economic expansions than in economic recessions. The margin is economically and statistically significant (Chordia & Shivakumar, 2002). Conversely, when the same model is employed by Griffin, Ji and Martin (2003), the model cannot explain momentum payoff in 16 countries, including the US. Furthermore, the study finds that momentum does well in both expansionary and recessionary economic cycles.

Cooper, Gutierrez, and Hameed (2004) use this same macroeconomic model and find it is not robust to out of sample data and that momentum is existent and significant regardless of what stage of the business cycle the economy is in. These results are in direct contradiction with Chordia and Shivakumar (2002) who conclude that changes in macroeconomic risk can explain momentum payoff through time. Market participants introduce momentum profits because they price this macroeconomic risk. On the other hand, the results of both Griffin *et al*., (2003) and Cooper *et al* (2004) suggest that macroeconomic factors, at least the ones identified by Chordia and Shivakumar (2002), do not explain the change in momentum payoff in time.

2.3.2 Momentum and Market State

Underreacting to information is a widely supported behavioural hypothesis for momentum, with over-reacting to information right up there with it. When market returns are high, the tide lifts investors with positions in individual shares. These investors convince themselves that the performance of their portfolios is due to their own brilliance and genius rather than luck. Sadly, this responsibility all but vanishes when markets crash, with investors blaming outside factors for disastrous losses in their portfolios. This is commonly known as a "self-attribution" bias and is hypothesised to be the cause of momentum (Daniel, Hirshleifer, & Subrahmanyam, 1998).

According to Gervais and Odean (2001), because the long positions are the majority of open position in stocks markets, a period with consistently increasing stock prices is largely beneficial for most investors. The upward price movement leads to portfolio gains, which causes investors to over attribute the gains to their own skill. Therefore, Gervais and Odean (2001) hypothesise that overconfidence is high immediately after the market experiences a gain. On the other hand, overconfidence is low following market losses.

As Daniel *et al.*, (1998) state, overconfidence triggers return continuation. Therefore, this provides the premise to Cooper *et al*., (2004). Increments in the payoff to momentum is preceded by months where the market was in a positive state. Therefore, the main objective of the paper is to test if momentum profits are significantly affected by market state in a predictable fashion. The market can either be in an “UP” market state or a “DOWN” market state. An “UP” state is one where the market has had a positive return in the last 36 months, otherwise the market is in a “DOWN” state.

The findings demonstrate that momentum payoff is contingent on market states. The results show that momentum profits are only significant in “UP” market states (Cooper *et al*., 2004). Momentum does not generate a significant profit following a “DOWN” market. Cooper *et al*., (2004) conclude that this result is consistent with Daniel *et al*., (1998) model where overconfidence leads to momentum. This is based on the interpolation of Gervais and Odean (2001) that overconfidence grows when markets are up, thus increasing the payoff to momentum.

These results are affirmed by Daniel and Moskowitz (2016) with very similar results showing that bear markets cause momentum payoffs to decline. To be precise, the paper finds that the portfolio market beta is the cause of the momentum crashes. What happens is that as shares get ranked based on their prior return, the shares that performed the best in up market state would be high beta shares. Due to the high sensitivity of high beta shares to the market, in a bull market, winner shares are likely to be high beta shares. Therefore, a winner portfolio will be loading up on high beta shares going into a market crash. Since these shares are highly sensitive to the state of the market, the momentum portfolio performs falls with the market during a downturn.

Conversely, after a market crash, shares that did poorly would be high beta shares. Therefore, a winner portfolio in a bear market would be buying low beta shares. The downside here comes with the loser portfolio, which would be short high beta shares following a market downturn. When the market makes a recovery, the high beta shares subsequently move up with the market, causing dramatic losses on the loser portfolio. Indeed, Daniel and Moskowitz (2016) show that the time variation in portfolio betas is extremely high.

As noted earlier, Avmarov *et al*., (2016) find that momentum payoff is larger when the state of the market is classified as "UP" as opposed to when the market is in a "DOWN" state. Furthermore, momentum becomes significant again, when market states are taken into consideration. Sagi and Seasholes (2007) use CRSP/Compustat data to simulate returns and perform numerical analysis on momentum portfolios formed with simulated returns. The findings indicate that momentum payoff is higher in up markets, with a return of 3.09%, than in down markets, which averages 0.20%.

Antoniou, Doukas and Subrahmanyam (2013) reveal insights that agree with the literature surveyed in this part of the chapter so far. After testing for a link between momentum payoff and investor sentiment, it is confirmed that high investor sentiment, coupled with equally high investor optimism, tends to push momentum profits upwards. The reverse is also true, with all round investor pessimism pushing momentum profits downwards. Furthermore, the monthly momentum payoff averages a statistically significant 2.00% when investor sentiment is optimistic, whereas the monthly momentum payoff averages a statistically insignificant 0.34% in times where investors are collectively pessimistic.

Antoniou *et al*., (2013) then proceed to test if market state and investor sentiment and jointly explain momentum payoff through time. Firstly, they confirm the results of Cooper *et al*., (2004), showing that momentum profits are, for the most part, insignificant in DOWN market states. Following this, momentum profits are calculated for optimistic and pessimistic periods in both UP and DOWN markets. With this two-prong classification, momentum profits are still insignificant in DOWN states irrespective of investor sentiment. In UP market states, momentum profits do vary depending on investor sentiment. The average payoff to momentum is at its highest in UP market states when investor sentiment is at its highest, with a statistically significant average momentum payoff of 2.12% in optimistic UP market states. In pessimistic UP market states, momentum strategies average an insignificant 0.87% monthly return.

In the UK, Galariotis, Holmes, Kallinterakis and Ma (2014) set out to ascertain the dependence, if any, of momentum payoff on market state. Using the same definitions given earlier, the paper tests if market state influences UK momentum payoff in a significant manner. The authors further add expectations and sentiment as potential explanatory variables for time varying momentum in the UK. In sharp contrast to the US literature, the size momentum payoffs through time is independent of market states. Furthermore, neither sentiment nor investor explanations can explain time variation of momentum payoff in the UK.

So, even with the persistence of the momentum anomaly, it has a weakness; it is potentially susceptible to the state of the market, critically exposing momentum to some dangerous crashes. Blitz, Huij and Martens (2011) find that momentum earned -8.5% from January 2000 to December 2009, mostly due to the massive losses in 2009. The authors use an alternative momentum construction, one that ranks shares based on the cumulative abnormal return rather than just the share return. This alternative momentum definition uses the Fama and French (1993) three factor model to get abnormal returns. This approach is lifted from Gutierrez and Prinsky (2007), who find that this form of momentum is just as significant as classical momentum. The crucial difference is that momentum based on factor residuals, hence termed residual momentum, does not reverse within a year like classical momentum. Blitz *et al*., (2011) show that residual momentum offers returns that are twice as large as returns from the classical momentum construction.

More important is that residual momentum is not as susceptible to market crashes as classical momentum. There are several reasons for this. Firstly, when momentum is formed using the Jegadeesh and Titman definition, characteristics of the momentum portfolios depends on the prevailing market state. During a bull market, the portfolio of winners will consist of high beta shares, whilst the portfolio of losers will consist of low beta shares. This is intuitive, shares that are highly sensitive to the market will perform extremely well when the market is doing well and vice versa. However, when the market state switches, high beta shares make losses, causing the high beta momentum winner portfolio to earn negative returns. The effect is exuberated on the WML portfolios as low beta shares do well and recover when the market makes a turn for the worse (Blitz *et al*., 2011).

Residual momentum sidesteps these issues by not loading up on high beta and low beta shares on winner and loser portfolios respectively. This is because residual momentum isolates the share specific momentum return, by excluding the market component. As a result, residual momentum is more crash proof than classical momentum, thus providing an avenue to circumvent the implications from Cooper *et al*., (2004).

Chaves (2016) takes a similar approach as Blitz *et al*., (2011), simplifying the methodology by using the CAPM to calculate abnormal returns, rather than the Fama and French (1993) three factor model. Chaves (2016) uses the excess returns to rank shares and sort into portfolios, creating idiosyncratic momentum strategy. Much like the classical momentum, the WML portfolio of idiosyncratic momentum is has a negative relationship with the market.

Chaves (2016) tests idiosyncratic momentum in 21 countries and finds that idiosyncratic momentum is present and strong in all countries, including Japan, where momentum has been known to fail. Furthermore, Chaves (2016) shows that idiosyncratic momentum does not have the same drastic losses due to market downturns that classical momentum has. This result is also found by Hanauer and Windmueller (2019), showing that idiosyncratic momentum is an effective guard against the losses that momentum experiences in bad market states.

Blitz, Hanauer and Vidojevic (2020) find that none of the well-known asset pricing factor models, including one with a momentum factor constructed using classical momentum, can explain idiosyncratic momentum. In fact, in some cases, classical momentum is subsumed by idiosyncratic momentum. The same cannot be said in the other direction.

Curiously, Blitz *et al*., (2020) findings demonstrate that, unlike classical momentum, idiosyncratic momentum does not reverse after a year. In fact, idiosyncratic momentum carries on for several years.

Furthermore, idiosyncratic momentum has lower volatility than classical momentum, whilst having a similar return profile. Consequently, the sharp ratio is much better. However, the key finding from the paper is that idiosyncratic momentum presents a significant buffer against market crashes because of the lower exposure to market states (Blitz *et al*,. 2020). Idiosyncratic momentum has positive returns in both positive and negative market states, although returns are not significant in the latter.

2.3.3 Momentum and Volatility

The literature surveyed so far shows that momentum delivers a return premium in multiple countries across the globe. However, Barroso and Santa-Clara (2015) make it known that there are extremely negative payoffs of momentum in periods of heightened market volatility. The paper provides evidence that in the US momentum strategies lost 73.42% in 2009. In 1932, the performance of the winner minus loser portfolio was even more disastrous losing 91.59% in just three months. Both periods experienced prolonged levels of high volatility.

Wang and Xu (2015) make the same observation as Barroso and Santa-Clara (2015), noting that extreme losses to a momentum portfolio in the period following the period of 2008 was the motivation for the study. In late 2008, Lehman Brothers filed for bankruptcy. This caused a ripple effect globally, with volatility reaching levels matched only by the 1929 market crash. The volatility appeared to affect the profitability of momentum with the payoff averaging a dismal -17% a month in the first half of 2009. This occurs because during highly volatile periods, there is a fundamental breakdown in momentum as loser stocks reverse hard and outperform winner stocks. Wang and Xu (2015) observe that momentum also breaks down during other periods of high volatility, with momentum performing poorly after the tech bubble blew up in the early 2000s and the volatile period of the early 1930s following the stock market crash of 1929.

Wang and Xu (2015) use this as a springboard to test if momentum payoff changes in accordance with the swings in volatility. Building on the methodologies of Chordia and Shivakumar (2002) and Cooper *et al*., (2004), volatility is used as the main explanatory variable of momentum profits through time. In addition to this, the paper tests volatility as an explanatory variable on a solitary basis. Wang and Xu (2015) redefine market state to historical six-month market return after observing that the Cooper *et al*., (2004) definitions does not result in an adequate number of down markets. The volatility used in the paper is the lagged twelve-month standard deviation of the daily market returns. The results show that by itself, volatility is significant in explaining the profitability of momentum returns. Furthermore, even with the inclusion of market state, macroeconomic and business cycle variables, volatility as an explanatory variable remains significant.

Additional results from Wang and Xu (2015) make known market state's insignificance in tests for predictive power of momentum. This is the case with both the six month and 36-month return of the market the base for calculating market states. This result contrasts with the results of Cooper *et al*., (2004), Sagi and Seasholes (2007), Antoniou *et al*., (2013), and by Daniel and Moskowitz (2016), which all find that market state has significant predictive power for momentum profits through time. However, Wang and Xu (2015) only consider one momentum strategy, which has a 12-month lookback period and a 1 month holding period, whereas the other papers consider multiple lookback and holding periods. With that being said, the one month holding period was done to avoid inducing autocorrelation in the monthly momentum returns.

Although market state was not significant, Wang and Xu (2015) find that market state and volatility work well to predict time variation in momentum payoff. This is especially true for volatility in the DOWN state. In all cases, the coefficients on volatility in the DOWN market state is of larger magnitude, has larger R-squared and t-statistic values. Wang and Xu (2015) state that market state and volatility jointly provide a good measure of market conditions.

Wang and Xu (2015) also note that there is asymmetry in the predictive power of volatility on time varying momentum profits. Specifically, volatility's predictive power is centred on loser stocks. This is not surprising considering the extreme reversals of loser stocks during highly volatile periods. However, this is not matched by winner stocks in low volatility periods.

Daniel and Moskowitz (2016) make many of the same observations as Wang and Xu (2015). For instance, Daniel and Moskowitz (2016) note that momentum experiences large crashes, which are most notable when market return in the previous twelve months was negative and when market volatility is high during these periods. This occurs because losers reverse hard and outperform past winners during this period. Additionally, Daniel and Moskowitz (2016), like Wang and Xu (2015), state that during volatile down markets, loser stocks behave almost like options, with asymmetric payoffs.

Wang and Xu (2015) struggle to provide a convincing reason as to why volatility is a predictor for momentum profits. Several volatility related measures are employed as explanatory variables to provide a theoretical reason for volatility. Of the measures used, only default risk absorbs some of the predictive power of volatility. Wang and Xu (2015) opine that in extreme market conditions, buying loser stocks is like buying options due to the asymmetric payoff structure. Investors buy loser stocks that appear to be cheap because the default risk has been overpriced by the market. In fact, it is shown that default risk and volatility have a correlation of 0.84 in DOWN markets.

An anomaly with the staying power of momentum is difficult to reconcile with risk-based explanations. This hints at a behavioural effect causing momentum, a point most of the literature on momentum agrees with. Thus, volatility is important to momentum because extreme volatility creates a shift in investor behaviour that causes momentum to crash. This then means that practitioners can implement momentum strategies using the predictable effect that volatility has on portfolios. Barrosoa and Santa-Clara (2015), Wang and Xu (2015) as well as Daniel and Moskowitz (2016), all use volatility and related measures to reduce the extreme returns of momentum.

This kind of explanation is the key difference between cross-sectional tests of momentum and time series tests of momentum. In the former, the cause of momentum is explored, in the latter factors that affect what causes momentum, and hence cause it to vary through time, are explored.

The literature on volatility is extensive, but that is outside of the scope of this study. Consequently, literature on spillover and contagion is ignored. The focus of the study is past market volatility on the JSE. As mentioned earlier, this study is the first of its kind on the JSE.

In South Africa, Page *et al*. (2013) state that the financial crisis of 2008 is likely to be cause of the lower profits of momentum from 1 January 2002 to December 2010. The financial crisis was a highly volatile period; hence volatility could have been the cause of the lower profits in that sample period. This would seem to suggest that volatility affects momentum profits through time. In the United States, during the financial crisis, momentum experienced reversals rather than continuation. That is, past winners became losers and past losers became winners. Therefore, the financial crisis is crucial as it demonstrates a fundamental breakdown in the momentum factor. It would be interesting to see if momentum experiences a similar breakdown in South Africa. If it does not, it would imply that momentum in South Africa has different drivers than the drivers of the momentum factor in the United States.

3 METHODOLOGY

This chapter describes the data and research methodology of this study. The methodology of this paper is primarily drawn from Wang and Xu (2015), with clearly stated reasons for any significant deviations or additions.

The sample period of Wang and Xu (2015) study is from August 1929 to July 2009, which was taken from the Kenneth French data library. Wang and Xu (2015) use the Fama and French (1996) methodology to construct momentum portfolios. This approach uses a lookback period of 12-months and only holds the portfolio for one month. The sorting procedure uses a decile ranking methodology, which sorts stocks into ten equally weighted portfolios. The winner minus loser difference forms the momentum payoff, MOM_t. Wang and Xu (2015) then use MOM_t to test for predictive power of volatility using the regression equation below:

$$MOM_t = a + b_0 x_{t-1} + \varepsilon_t \tag{1}$$

where MOM_t is the momentum payoff in month *t*, and x_{t-1} is one of the predictor variables, which are computed in month *t-1*. The main predictor variables used by Wang and Xu (2015) are volatility, market state and volatility in different market states. Initially, univariate regressions are performed to test the explanatory power of each variable. The variables are then used in conjunction to see if any of the variables remain statistically significant in the presence of the other variables.

The rest of this chapter is structured as follows; Chapter 3.1 describes the data used in the tests as well as the momentum portfolio construction. Chapter 3.2 describes the tests for explanatory power of volatility and market state on momentum.

3.1 DATA COLLECTION AND SAMPLING

3.1.1 Data for momentum portfolios

The data, which was collected from Bloomberg, comprises of daily observations of stock prices, market capitalisations, number of shares, and trade volume. The sample period on this data is from August 1998 to October 2019. The reason for the start date of January 1998 is that data on the All Share Index (ALSI) only begins in July 1995. Therefore, a date earlier than August 1998 would mean that there would be no data to create a market variable under a thirty-six-month definition. This is also necessary for the refined momentum strategy, which compares the 12-month market volatility to the 36-month market volatility to determine if a month is in a low or high volatility month. The sample ends in October 2019 because, the last full month of data was October 2019 when data was collected.

The data has been adjusted for dividend payments and distributions. This is done by simply adding the cash payment amount to the price on the trading day immediately after the last date to register. The database has no survivorship bias, as shares that are delisted are included in the dataset. When dealing with historical data, one must take care to construct strategies using information that a trader would have had at the time of portfolio construction. For instance, a trader would not know in advance which share would delist when forming a portfolio.

Therefore, a penalty of -100% is imposed if a share experiences a delisting while the in a portfolio. No other adjustments have been made.

3.1.2 Data for explanatory variables

Data is also required on the explanatory variables. The dividend yield on the value weighted ALSI is sourced from Bloomberg. The yield on the 10-year Treasury note is proxied by the GSB10YR index, sourced from Bloomberg. The SARB provides the historical yield on the 91-day Treasury bill on their online database, so this data was retrieved for use in this study. The South African Volatility Index (SAVI) is a forecast of volatility of the South African market. Data on the SAVI is only available from 2007 as that was the year of its inception. Therefore, regressions with the SAVI as an explanatory variable will exclude momentum returns prior to 2007 and any other variables included with the SAVI will also exclude data prior to 2007. Bloomberg is also the source of data on the SAVI.

The variables described in this chapter are used as control variables in the regression to test if these variables can absorb the explanatory power, if any, of volatility. In addition, these variables may aid in explaining why volatility is significant in the regressions, if it is found to be significant.

The business cycle variables are the dividend yield on the ALSI (DIV), the difference between the 10-year Treasury note and the 91-day Treasury bill (TERM), and the yield on the 91-day Treasury bill (YLD). These variables are included because Chordia and Shivakumar (2002) find that macroeconomic factors are able to explain time varying momentum payoffs. Wang and Xu (2015) show that these variables are not statistically significant when included with volatility but could offer theoretical explanations for the significance of volatility. The variables are included in this study for this reason.

The study uses a Hodrick-Prescott filter developed by Hodrick and Prescott (1997) to decompose the business cycle variables to remove the trend component. Once this is applied, the series is split into a trend component and a cyclical component, i.e. the business cycle. The cycle component shows the deviations from the trend. Therefore, if the data point value is above the trend, the cyclical component will be positive and vice versa. A positive value indicates that the economy is in a boom cycle while a negative value indicates that the economy is in a bust cycle. The cyclical component of the business cycle variables is then used to divide the sample into expansionary and recessionary periods.

Merton Default Probabilities

To calculate probabilities of default, the model introduced by Merton (1974) is employed. This model treats shareholding in a firm like a call option on company assets. Since debt holders are residual claimants, owners of a company's equity securities can only receive a payment in a liquidation event after debt holders are paid in full. Therefore, owning a company' non-debt securities is like having a call option where the company's assets are the underlying asset. The call option is in the money if the firm value is above total debt and out the money if firm value is below the total debt. In the latter case, debt holders are the de facto owner of the firm. It is this optionality, i.e. the option to abscond from total liability when the firm's debts exceed the firm's assets, that gives equity an implicit call option.

Since equity is a call option, one can use the Black-Scholes option pricing formula developed by Black and Scholes (1973). The value of the equity is then given by the equation below:

$$E = VN(d_1) - De^{-rt}N(d_2) \tag{2}$$

Where E is the value of equity, V is the value of assets, D is the value of debt, and r is the risk free rate. The value of d_1 is given by:

$$d_1 = \frac{\ln\frac{V}{D} + \left(r + \frac{1}{2}\sigma_V^2\right)T}{\sigma_V . \sqrt{T}} \tag{3}$$

And d_2:

$$d_2 = d_1 - \sigma_V \sqrt{T} \tag{4}$$

Where σ_V the volatility of asset value and T is the maturity of the debt, which under the Merton (1974) model is one year. That is, the probability of default is calculated assuming default occurs within a year. Both asset value and asset volatility are not directly observable, therefore there are two unknowns. However, both equity value and equity volatility are directly observable market variables. Hence, equations 7 and 8 can be manipulated to simultaneously solve for the value of assets and asset volatility.

Once the asset value and asset volatility have been estimated, d_1 is calculated. This is the distance to default under the Merton (1974) model. Therefore, probability of default is given by:

$$1 - N(d_1) \tag{5}$$

Data required to calculate Merton default probabilities comprises of the dividend yield, long-term debt and short-term debt.

FEARS Index

The FEARS index replaces the investor sentiment index, developed by Baker and Wurgler (2006), used in Wang and Xu (2015). This is because Solanki and Seetharam (2018) find that in a macroeconomic APT model, the FEARS index is significant in explaining market returns in South Africa. The FEARS index is constructed using internet search history of households from Google. Google publishes search trends via Google Trends for households in multiple countries, including South Africa. The data is available for download via the Search Volume Index (SVI), which shows the number of searches for various key terms. This means that the SVI can be used to measure investor sentiment directly because it captures first hand data of what individuals in an economy are thinking of. Da, Engleberg and Gao (2015) use economic and finance associated words that are either positive or negative to return SVI data for households. This then gives investor sentiment as the search trends shows to what extent people are worried or optimistic via the level of searches for words like “recession” and “inflation”. Da, Engleberg and Gao (2015) then calculate the daily log differences to get the change in SVI:

$$\Delta SVI_{j,t} = \ln\left(SVI_{j,t}\right) - \ln\left(SVI_{j,t-1}\right) \tag{6}$$

where $SVI_{j,t}$ is the SVI of a search term *j* and time *t*. Since this paper uses monthly periods as does Solanki and Seetharam (2018), the SVI needs transformation into a monthly series before differencing. Following Solanki and Seetharam (2018), the data is transformed to monthly by taking a weekly average:

$$SVI_{monthly} = SVI_1 + SVI_2 + SVI_3 + \cdots + SVI_n \tag{7}$$

Da, Engleberg and Gao (2015) show that the SVI data has heteroscedasticity, seasonality and extreme observations. To solve these issues, the data is winsorised, deseasonalised and standardised to give an adjusted SVI ($\Delta ASVI_{j,t}$) for each of the search terms. Finally, the $\Delta ASVI_{j,t}$ is regressed on lagged market returns to determine the most significant search terms. Both Da *et al*., (2015) and Solanki and Seetharam (2018) find that the most significant search terms are almost always negative. Therefore, the FEARS index is the sum of the top 30 significant search terms:

$$FEARS_t = \sum R_i(\Delta ASVI_t) \quad (8)$$

Sentiment might be linked with volatility. The rationale behind this is that investor sentiment might lead volatility swings. For instance, if the sentiment indicates that investors are "fearful", this would indicate that there might be large selling pressure on the horizon, which induces volatility. Investor sentiment may aid in explaining why the momentum factor breaks down (if it does on the JSE like in the US). If the existence of the momentum factor is due to behavioural biases, then as sentiment approaches "fearful", the behavioural biases that cause the momentum factor are overwhelmed by investors fearing a market crash. This coincides with volatility, creating a structural break in the momentum factor. This is pure conjecture at this point, but if sentiment is found to be linked with volatility in this regression, this may present some evidence for this conjecture.

Traditionally, SAVI is used as a sentiment index on the JSE. However, in this study it is used as a forward looking measure of volatility in order to serve as a volatility replacement. For this study, FEARS is a sentiment index that is a forward looking measure of overall market conditions.

3.1.3 Exclusions and Adjustments

Even though this research is replicating the methodology of Wang and Xu (2015), the focus is on the JSE. As such, it is prudent to make additions to the methodology based on prior momentum research on the JSE. For instance, Page and Auret (2017) test variations of momentum methodologies on the JSE. This paper was an attempt to search for the optimal momentum methodology on the JSE. The paper finds that the difference in returns of methodologies applying a price filter of 0 cents and 100 cents is significant as the 100 cents price filter portfolio outperforms the 0 cents price filter portfolios in 88% of the simulations. This suggests that transaction costs eat away at momentum profits. Furthermore, the paper finds that in the case of equal weighting, complemented by ignoring the most recent month during share rankings, the portfolios with the high liquidity price filter beat the low liquidity price filter portfolios in 58% of the simulations. This percentage becomes higher, 63% for equal weighting and no gap between ranking and portfolio formation.

Cooper *et al.*, (2004) use a $1 price filter to avoid microstructure effects common with low price stocks. Page and Auret (2017) combine the price filter and liquidity filter for two reasons. The price filter is implemented with transaction costs in mind. The price filter eliminates stocks that would have high transaction costs thereby adding realism to the study. The liquidity filter deals with illiquid stocks. The intersection of both filters reduces the momentum portfolios sensitivity to transaction costs and liquidity (Page & Auret, 2017).

This study employs both the price filter and the liquidity filter for the same reasons as Page and Auret (2017). The price filter is the extreme filter used in Page and Auret (2017), which is a minimum price of R1. The liquidity filter is also the one used in Page and Auret (2017). This filter sets the maximum daily zero trades to 100. In addition, if a share that has a trading volume below the 10^{th} percentile of mean historical turnover, it is excluded (Page & Auret, 2017). Thus, if a share's zero daily trades exceed the one hundred days limit in the prior year and/or it is in the bottom 10^{th} percentile of historical average turnover, it is excluded. Note that the turnover restriction is not a third separate filter but rather is used to enhance the liquidity filter.

An additional restriction is that there must be return data from twelve months prior to the sort date. A return of -100% is assigned if a share delisted in the month that it delisted and 0% thereafter.

3.1.4 Momentum Portfolio Construction

This research employs the same lookback periods as Jegadeesh and Titman (1993) to sort stocks into momentum portfolios. Based on Page and Auret (2017) methodology, the stocks are sorted into five quintile portfolios. The sorting procedure is based on stocks prior returns from *t-n* to *t-1*. Thus, the methodology ranks stocks on their prior 3, 6, 9 and 12-month return. The momentum construction skips a month between portfolio formation and the sort date to sidestep the microstructure effects described earlier. Therefore, momentum is defined at time *t* as:

$$Momentum_i = \sum_{t-n}^{E} R_{i,t-n-1} \quad (9)$$

Where *E* is the estimation period, *t* is the formation date, *n* is the number of months to lookback on.

The holding period for the portfolios is only one month. This is because, according to Wang and Xu (2015) a holding period of only month makes this formation ideal for time series tests. This is because a holding period of longer than one month creates autocorrelation, which makes for spurious regressions. This is of little consequence to momentum returns as Fama and French (1996) show that this construction still produces unexplained abnormal profits. On the other hand, Page and Auret (2017) find that the rank on 6-months and hold for 6 or 9-months produces the highest returns regardless of price filter, liquidity filter or gap between portfolio formation and holding period. However, this study is concerned with the explanatory power of volatility and not the momentum factor itself.

The sorting procedure is only performed on the largest 100 shares by market capitalisation on the sort date. The reason for this is because small illiquid shares have large percentage changes. This skews the momentum sorts as both the winner and loser portfolios might contain several shares that have high trading costs, such as wide bid-ask spreads, low number of bids among other factors. Lastly, the portfolios use both equal weighting and value-weighted portfolios, as a robustness check.

3.1.5 Portfolio returns

Monthly portfolio returns are calculated by cumulating the daily returns on the stocks in the portfolios for each month. When the portfolios are constructed, each share is allocated an initial weight in the portfolio. For equally weighted portfolios, each share has a weight of *1/n*. For value weighted portfolios, the weight for a share in a portfolio is given by the market capitalisation of the share on the portfolio formation date divided by the total market capitalisation of all the shares in the portfolios. The portfolio return is given by:

$$PFR_t = \sum_{i=1}^{n} W_{i,t-1}(1 + r_{i,t}) \tag{10}$$

Where PFR_t is the portfolio return at time t, n is the number of shares in the portfolio, $W_{i,t-1}$ is the initial weight of each share assigned on the portfolio formation date, and $r_{i,t}$ is the return on the stock for the month at time t.

Following Wang and Xu (2015), the portfolios will only be held for one month. Wang and Xu (2015) provide reasons for this, one being that since Fama and Frech (1996) fail to attribute the returns to momentum from this strategy to common risk factors, this momentum formation is as robust as the strategies from Jegadeesh and Titman (1993). Another reason is that a one month holding period in momentum strategies is ideal for time series tests of predictive power. For time series tests to be conducted, monthly observations of momentum payoff are required, and autocorrelation between the observations should be low or none-existent. Wang and Xu (2015) argue that holding periods longer than 1 month might artificially induce autocorrelation in the series.

On the other hand, Page and Auret (2017) find that the rank on 6-months and hold for 6 or 9-months produces the highest returns regardless of price filter, liquidity filter or gap between portfolio formation and holding period. However, this paper study is concerned with the explanatory power of volatility and not the momentum factor itself. As mentioned earlier, the concern here is with time variation in the profits to momentum. Therefore, the main interest is to test if the difference in momentum payoff through time can be explained by increases and decreases in market volatility and/or market state.

3.2 DESCRIPTION OF METHODOLOGY

This sub section describes the construction of momentum portfolios, the tests that will be used to uncover explanatory power of volatility and market state. All variables used in the tests are defined here.

3.2.1 Univariate regressions

The study tests for the explanatory power of the variables of market state and market volatility. For the purposes of this study, volatility here is not to be confused with idiosyncratic risk. This is volatility of the market as a whole and not on an individual stock basis. Wang and Xu (2015) found that market state has no explanatory power in the United States neither on a solitary basis nor when volatility and market state are used together. Therefore, this study also serves as the first to test for the explanatory power of market state for momentum profits on the JSE. Regressions are of the form:

$$MOM_t = a + \beta_0 UP_{t-1} + \varepsilon_t \tag{11}$$

where MOM_t is the momentum payoff in month *t*, defined as the return on the winner's portfolio minus the return on the loser's portfolio, UP is the explanatory variable of market state. Market state is defined using the lagged 6-month return on the market, if the lagged 6-month return is positive, UP is equal to 1, otherwise it is equal to 0. It is important to note that

UP is lagged, therefore, it is computed at month *t-1*, for use in regressions with momentum payoff at month *t*.

The study tests if volatility is significant by itself in explaining time varying momentum profits with the regression below:

$$MOM_t = a + \beta_0 Vol_{t-1} + \varepsilon_t \tag{12}$$

where MOM_t is the momentum payoff in month *t*, defined as the return on the winners portfolio minus the return on the losers portfolio, Vol is the explanatory variable volatility, defined as the lagged 12-month market volatility. This is a rolling standard deviation of daily returns, which means that after each holding period (i.e. every month), Vol_{t-1} is the standard deviation of the daily returns of the market in the previous 12-months at *t-1*. Therefore, Vol_{t-1} is not an average.

3.2.2 Multivariate regressions

The two main variables of interest are market state and market volatility. The two variables are evaluated in separate univariate regressions. This study also uses a multivariate volatility regression model, which separates volatility based on market state, defined as:

$$MOM_t = a + \beta_0 Vol_{t-1}^{+} + \beta_1 Vol_{t-1}^{-} + \varepsilon_t \tag{13}$$

where MOM_t is the momentum payoff in month *t*, defined as the return on the winners portfolio minus the return on the losers portfolio, $Vol_{t-1}^{+}$is equal to Vol if the lagged 6-month return is positive and zero otherwise and Vol_{t-1}^{-} is equal to Vol if the lagged 6-month return is negative and zero otherwise.

3.2.3 Granger causality tests

Granger causality is tested for with the method developed by Granger (1969). This is necessary to identify if each of the explanatory variables are granger caused by momentum and vice versa. This is performed as a preliminary data check to test collinearity. The tests are of the form:

$$MOM_t = \alpha_0 + \alpha_1 MOM_{t-1} + \cdots + \alpha_l MOM_{t-l} + \beta_1 UP_{t-1} + \cdots + \beta_l UP_{t-l} + \varepsilon_t \tag{16}$$

$$MKT_t = \alpha_0 + \alpha_1 UP_{t-1} + \cdots + \alpha_l UP_{t-l} + \beta_1 MOM_{t-1} + \cdots + \beta_l MOM_{t-l} + \varepsilon_t \tag{17}$$

$$MOM_t = \alpha_0 + \alpha_1 VOL_{t-1} + \cdots + \alpha_l VOL_{t-l} + \beta_1 MOM_{t-1} + \cdots + \beta_l MOM_{t-l} + \varepsilon_t \quad (18)$$

$$Vol = \alpha_0 + \alpha_1 MOM_{t-1} + \cdots + \alpha_l MOM_{t-l} + \beta_1 Vol_{t-1} + \cdots + \beta_l Vol_{t-l} + \varepsilon_t \quad (19)$$

The study also performs Granger causality tests on the control variables using:

$$MOM_t = \alpha_0 + \alpha_1 x_{t-1} + \cdots + \alpha_l x_{t-l} + \beta_1 MOM_{t-1} + \cdots + \beta_l MOM_{t-l} + \varepsilon_t \quad (20)$$

$$x_t = \alpha_0 + \alpha_1 x_{t-1} + \cdots + \alpha_l x_{t-l} + \beta_1 MOM_{t-1} + \cdots + \beta_l MOM_{t-l} + \varepsilon_t \quad (21)$$

Where x_t is one of the control variables.

3.2.4 Other data preparation checks

Prior to proceeding with time series tests, the data needs to be checked for autocorrelation. Autocorrelation means that an observation at a point in time is dependent on an observation at a previous point in time. Tests for autocorrelation are performed using an autocorrelation function, which plots the correlation against the lag length. Tests for unit root are also performed.

The regression method used in the tests is the Ordinary Least Squares (OLS) linear regression model. The main explanatory variables are volatility, market state and volatility in UP and DOWN market states. The dependent variable is the payoff to momentum at time *t*. The entire methodology is implemented using the statistical software R. The full list of control variables is given below:

DIV_{t-l}: Dividend yield on the market index

$TERM_{t-l}$: The difference between the yield on the 10 year note and 91-day Treasury bill

YLD_{t-l}: The yield on the 91-day Treasury bill

$SAVI_{t-l}$: The South African Volatility Index

$SEMI_{t-l}$: Semi-deviation or downside deviation, which is a measure of downside risk

RD_{t-l}: Return Dispersion

$FEARS_{t-l}$: Measure of investor sentiment

DEF_{t-l}: Merton model default probabilities

These will be explained in the proceeding chapter.

3.2.5 Robustness Checks

This study seeks theoretical explanations for the results using other variables related to volatility and market states. These are the SAVI, the Financial and Economic Attitudes Revealed by Search (FEARS) index of Da, Engleberg and Gao (2015), the Merton default probabilities (DEF), semi-deviation (SEMI) and return dispersion (RD). The variables SAVI and SEMI serve as proxies for volatility, while the rest are included with volatility to test if the explanatory power of volatility changes in the presence of these control variables.

If market volatility and/or market state is significant, then these variables can explain why volatility and/or market state affects momentum profits. For instance, return dispersion is cross-sectional standard deviation, which is a test for herding. Stivers and Sun (2010) use RD to test if it can explain time variation in momentum payoff. They find RD to be significant, which leads Wang and Xu (2015) to include RD in their empirical tests. This study does the same for similar reasons.

If volatility is significant in the regression and RD absolves some of the predictive power of volatility, then it might be hypothesised that herding behaviour is the reason why volatility causes a breakdown in the momentum factor. Although RD is a cross-sectional measure, a time series of changes in RD through time is constructed for the tests. Return dispersion at time *t* is calculated using the equation below:

$$\sqrt[2]{\frac{\sum(R_i - \bar{R})^2}{N}} \tag{22}$$

Where R_i is the return on stock i at time *t*, $\bar{R}$ is the average return of all stocks at time *t*, and *N* is the number of stocks at time *t*.

In order to ensure that the results are robust, additional tests are performed with portfolios constructed based on momentum and size. Shares are sorted into two size portfolios. The shares are sorted into large if they are in the top 50 shares by market capitalisation, otherwise the shares are sorted into small. Both size portfolios have winner and loser portfolios, such that momentum portfolios are created to be momentum big and momentum small. Momentum is constructed in the same manner as before and all lookback periods are considered. Additionally, both equally weighted and value weighted schemas are employed. Further robustness checks include using the 36-month market state definition originally given by Cooper *et al*., (2004) and the lagged 6-month market volatility.

3.3 LIMITATIONS

A major limitation of this study is the methodology applied to determine market states. The current measures only consider values over a moving window, without additional layers to test extremity of the market state. This potentially leads to understated market states, particularly for down market states. This in turn affects the effectiveness of volatility in the down state.

This study ignores spillover effects and contagion as only past volatility of the JSE is considered as a variable. The assumption made is that any spillover effect is captured in this past volatility.

3.4 SUMMARY

A summary of all regressions to be performed is provided in Table 1 below.

Table 1 Summary of regressions to be performed

	Model	Dependent Variable	Independent Variable 1	Independent Variable 2
1	Univariate volatility	Momentum	Volatility	
2	Univariate market state	Momentum	Market State	
3	Multivariate volatility in market state	Momentum	Volatility in up state	Volatility in down state
4	Control	Momentum	Volatility	Control variable
5	Volatility proxies	Momentum	SEMI/SAVI	Market State

The methodology of this study is adapted from Wang and Xu (2015) in order to test the effect of volatility and market state on momentum payoff through time on the JSE. It is important to note that the sample size of this study is much smaller than the Wang and Xu (2015) study. Nevertheless, momentum is still significant on the JSE even with a smaller sample. Furthermore, Wang and Xu (2015) show that the 2008 period is a key factor in their results. The sample used in this study includes the 2008 period, which means that the smaller sample size should not negatively affect the results.

The chapter that follows, Chapter 4, presents the results from the tests described in this chapter. In addition, an in-depth discussion of the results is provided.

4 RESULTS

This chapter reports the results of the tests described in Chapter 3. The results chapter is broken up into six main sections. Chapter 4.1 provides a rudimentary analysis of momentum and volatility graphs in order to justify subsequent in-depth statistical tests. Chapter 4.2 describes the main results of the study, which is the regression of momentum payoff on market volatility and market state. Chapters 4.3 presents results from regressions using measures that are related to volatility. Chapter 4.4 shows results of regressions with sentiment and return dispersion. Chapters 4.5 shows the results of univariate regressions of momentum and default risk. Chapters 4.6 and 4.7 report the results from the robustness checks, with Chapter 4.6 detailing results from regressions on momentum constructed with size portfolios and Chapter 4.7 showing results from using different window periods on both volatility and market. The performance of the refined momentum strategy is reported in Chapter 4.8. The results are deliberated at length in Chapter 4.9, which attempts to provide theoretical explanations for the results.

4.1 PRELIMINARY RESULTS

Table 2 shows the average monthly percentage return to each portfolio. The 3 columns with equal in the brackets show results of equally weighted portfolios. The last three columns show results from value weighted momentum portfolios.

The table demonstrates that momentum strategies deliver high returns. The best strategy is the 12 month equally weighted portfolio, which delivers an average of 2.07% per month, which is roughly 25% per year.

This differs slightly from Page and Auret (2017), who find that the best performing strategy is the 6-month strategy, with a holding period of 9 months. This might be because Page and Auret (2017) hold portfolios for 3, 6, 9 and 12 months, whereas this study only holds shares in a portfolio for a month.

On the other hand, the results show that equally weighted portfolios outperform value weighted portfolios across the board. This finding is in line with the findings of Page and Auret (2017), who also find that equally weighted portfolios deliver higher returns.

Table 2 Average monthly momentum returns (%)

Lookback period	Winner (Equal)	Loser (Equal)	WML (Equal)	Winner (Value)	Loser (Value)	WML (Value)
3 Month	1.456	0.811	0.645	1.179	0.932	0.247
6 Month	1.758	0.529	1.229	1.474	0.853	0.621
9 Month	1.910	0.541	1.368	1.535	0.452	1.083
12 Month	2.070	0.490	1.580	1.758	0.435	1.323

The table below shows the results of the t-test of the winner minus loser difference in means. The results show that all the equally weighted portfolios produce significant momentum returns. In contrast, just two out of the four value weighted portfolios produce statistically significant returns. Furthermore, each equally portfolio produces a larger statistic over its value weighted counterpart.

Table 3 T-Test of Winner minus Loser difference in means

Lookback	Weighting	statistic	p value
3 Month	Equal	1.971	0.050
3 Month	Value	0.555	0.579
6 Month	Equal	3.415	0.001
6 Month	Value	1.376	0.170
9 Month	Equal	3.895	0.0001
9 Month	Value	2.639	0.009
12 Month	Equal	4.450	0.00001
12 Month	Value	3.085	0.002

In order to ascertain if further investigation is warranted, a simple graphical analysis is performed on the payoffs of the winner and loser portfolios. Figures 1 shows the cumulative performance of investing R1 in the equally weighted winner and loser portfolios from January 1998 to December 2018, constructed by 12-month prior return. The figure also shows the drawdowns of each portfolio as well as the period returns. Analysis of this figure provides motivation for in depth analysis of momentum and volatility. This portfolio is included because it achieves the largest return as well as being the most statistically significant momentum portfolio.

Figure 1 shows that there has been a monotonic decrease in the payoff to the winner portfolio through time, a result that was also found by Page *et al*., (2013). This decrease is clear in spite of the large and statistically significant return of the 12 month equally weighted portfolio. The drawdowns demonstrate that the losers reverse harder than winners during the 2008 financial crisis. Wang and Xu (2015) postulate that this leads to a breakdown of the momentum factor. This suggests that volatility might be related to momentum profits. In 2015, the loser portfolio experiences extreme reversals. The period returns graph shows that losers had much higher returns than the winner's portfolio. This shows the implicit risk to following a momentum strategy, one is taking the risk that losers will not reverse. During crises, market participants may buy up cheap stocks that appear to be cheap in order to profit from a potential future gain. This hints at a behavioural effect being the cause of the existence of the momentum effect.

Figure 2 shows the performance of the winner and loser portfolios during the financial crisis period. This is the same strategy used in Figure 1. The losers reverse and recover losses quicker than the winners, with the winners only recovering in late 2010. With that being said, this only occurs during the financial crisis and in 2015. The years 1999 and 2001 had high levels of volatility following the Asian financial crisis and the tech bubble crash respectively.

Figure 3 plots the monthly standard deviation of daily market returns and the momentum payoff. Towards the end of 2008, volatility surges following the collapse of Lehman Brothers. Although volatility peaks during this period, it remained high until halfway through 2009. The figure reveals an interesting fact, the most negative return on the winner minus loser portfolio precedes the period with the highest volatility. The months with a standard deviation of 15% or more are followed by two months of positive momentum payoffs.

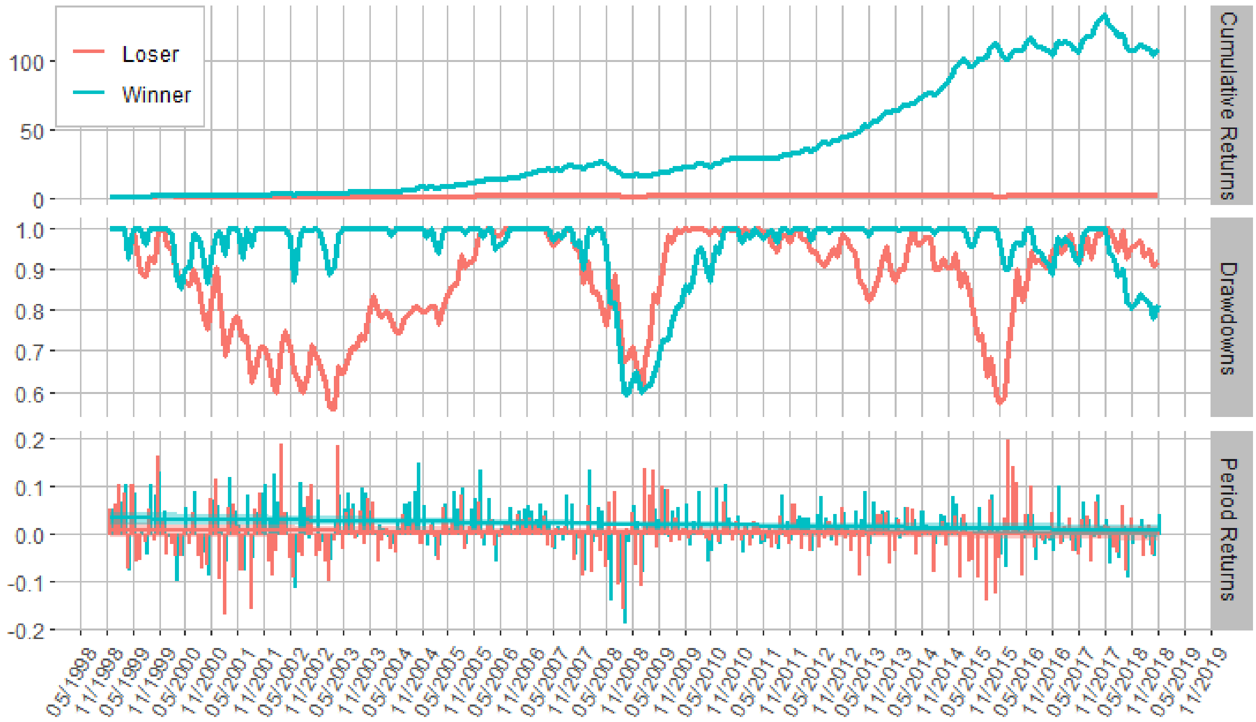

Figure 1 Cumulative Performance of R1 investment in the Equally Weighted Winner and Loser Portfolios of 12-month Momentum

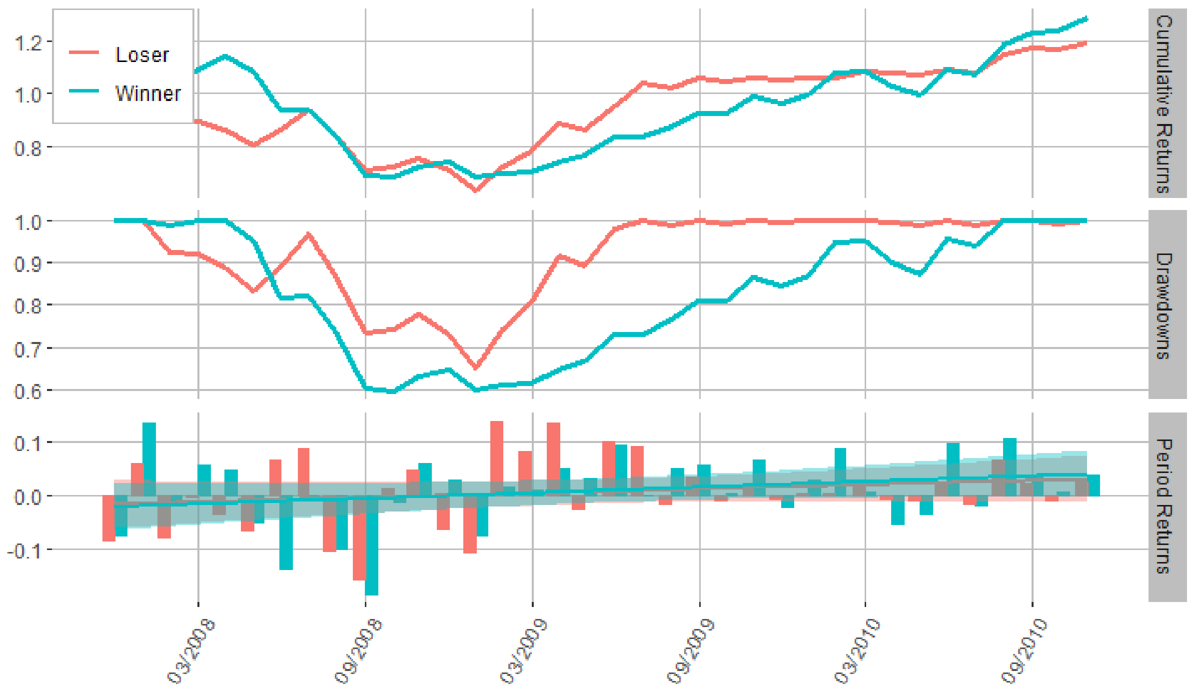

Figure 2 Cumulative Performance of R1 investment in the Equally Weighted Winner and Loser Portfolios of 12-month Momentum from 2008 to 2010

Wang and Xu (2015) document the reverse occurrence, with momentum payoff having the most negative returns following the most volatile months. However, for the JSE, it would appear that an increase in volatility does not lead to a decrease in momentum payoff. For instance, the most extreme negative momentum payoff happens after 6 consecutive months of descending volatility. As can be seen more closely from Figure 3, the loser's reversal occurs during the most volatile months of late 2008.

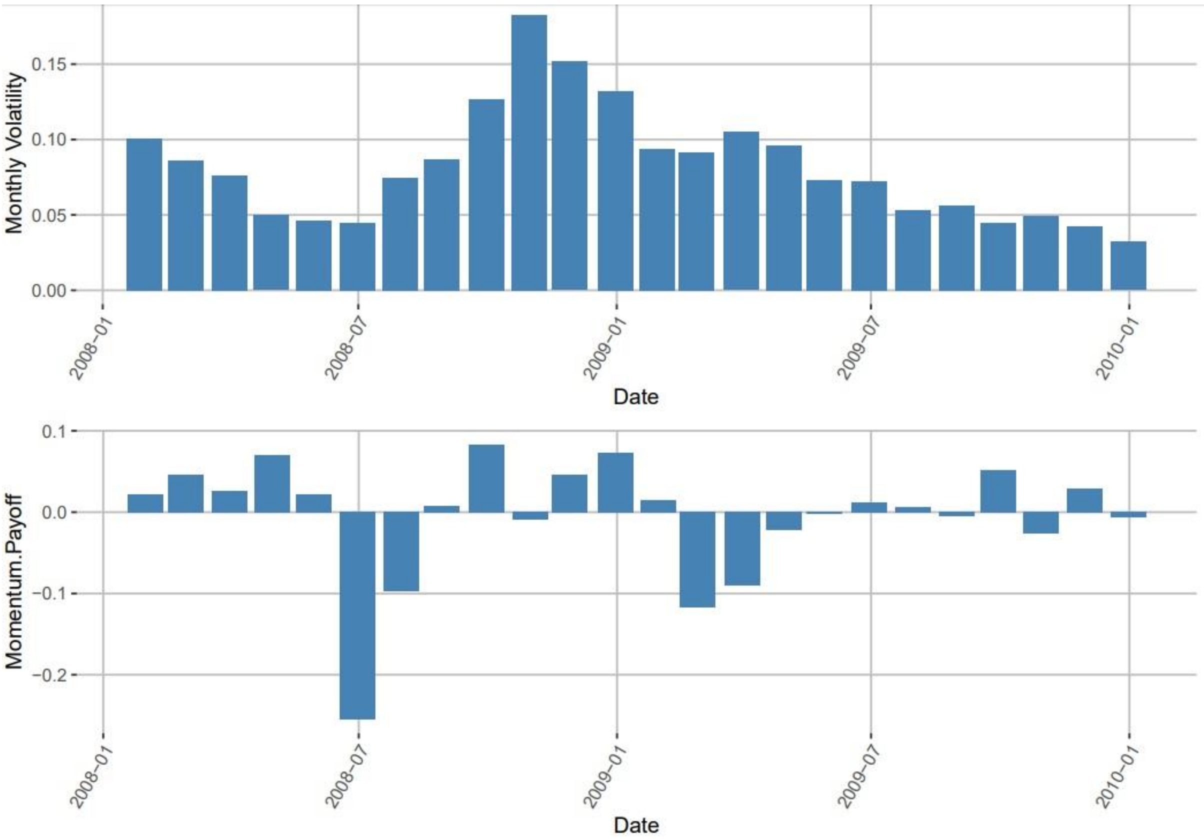

Figure 3 Market volatility and momentum payoff during 2008–2009 financial crisis

Figure 4 shows the cumulative performance of the 6-month value weighted portfolio. The 6-month portfolio shows similarities with the 12-month equally weighted portfolio, particularly with the drawdowns during the financial crisis. The drawdowns show that the losers reverse at a quicker rate than the winners.

In contrast to the 12-month equally weighted portfolio, the 6-month equally weighted portfolio also experiences the same phenomena during the Asian financial crisis of the late 1990s. The drawdowns show that the winners portfolio suffers a substantial loss, down as much as 40% during the period. Furthermore, the portfolio does not recover until after nearly a year. The loser portfolio on the other hand, does not suffer such a severe crash during the same period. In fact, the graph shows that losers are reversing just as the winner portfolio crashes. Indeed, the loser portfolio has several large positive returns during the period. This matches with the momentum crashes documented in the US literature. In addition, this hints at the 6-month portfolio being more likely to have a significant coefficient on volatility, given that volatility seems to affect this portfolio more than the 12 month equally weighted portfolio.

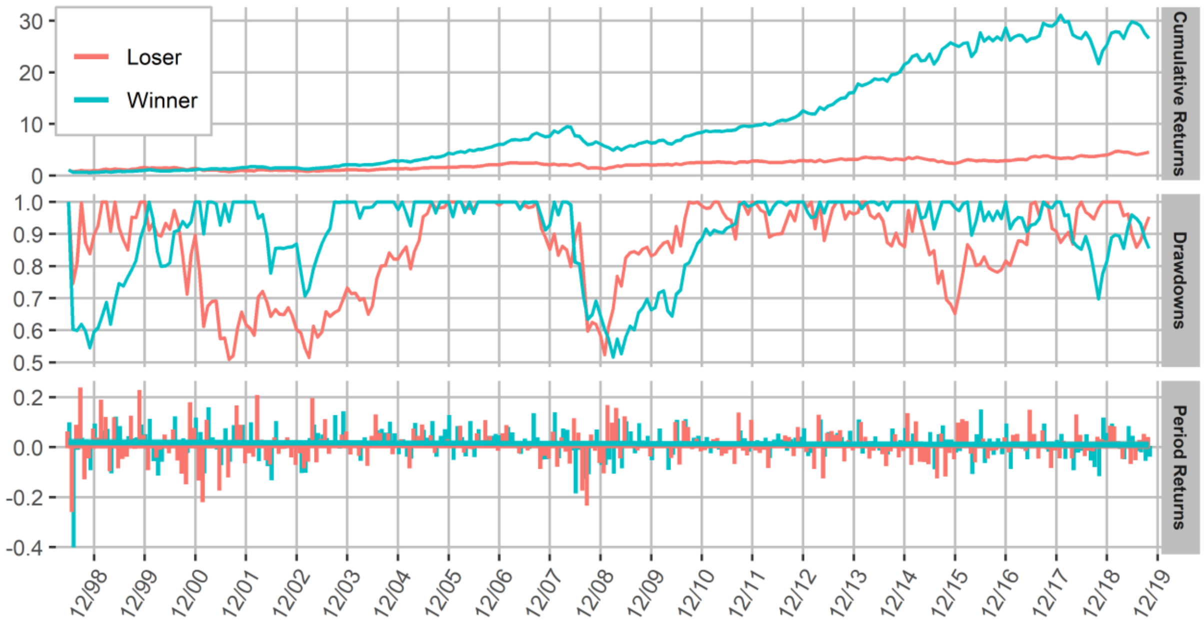

Figure 4 Cumulative Performance of R1 investment in the Value Weighted Winner and Loser Portfolios of 6-month Momentum

Table 4 shows the monthly momentum payoff for the full sample, in up market states and downmarket states. All values in the table are in percentages. Momentum is constructed using the past 3, 6, 9 and 12-month returns. The holding period is one month and both equally weighted and value weighted portfolios are considered.

The results show that equally weighted portfolios achieve higher mean monthly returns across all four lookback periods. This result is in line with the results of Page and Auret (2017) who found that equally weighted portfolios outperform value weighted portfolios.

The results in Table 4 are counterintuitive because they seem to suggest the state of the market has no effect on momentum. This contrary to the results of Cooper *et al* (2004), who find that momentum has higher returns in positive market states than in negative market states. But then on the JSE, as shown in Table 4 below, only the 3-month strategy performs worse in a down market state than in an up market state for equally weighted portfolios. The rest of the equally weighted portfolios have higher returns in negative market states than in positive market states. For value weighted portfolios, the 3 and 6-month return perform worse in down markets than in up markets, while the 9 and 12-month portfolios perform better in down markets than in an up-market state. Furthermore, the 3-month average momentum payoff with value weighting is the only portfolio with a negative payoff in a down market state.

Table 4 Monthly Momentum Payoff (%)

Equally Weighted	3-month momentum	6-month momentum	9-month momentum	12-month momentum
Full Period	0.696	1.075	1.327	1.608
Up State	0.892	0.994	1.127	1.530
Down State	0.367	1.307	1.650	1.708
Value Weighted	**3-month momentum**	**6-month momentum**	**9-month momentum**	**12-month momentum**
Full Period	0.351	0.598	1.023	1.565
Up State	0.899	0.906	0.936	1.500
Down State	-0.324	0.490	1.273	1.649

4.1.1 Granger Causality Tests

Granger causality tests are performed between momentum and each of the x variables. This is done in order to detect any potential collinearity between momentum and each of the x variables as well as the control variables. Table 3 below presents the p-values from the Granger-causality tests from lags 1 to 7. For each lag, the null hypothesis that momentum does not Granger cause market state and volatility cannot be rejected. This is also the case in the reverse direction. Therefore, bidirectional causality does not exist between momentum and market state or volatility. The momentum strategy used in Table 5 is the 6-month value weighted strategy, reported here as it is the main strategy of interest in the chapter that follows.

Table 5 Granger-Causality Tests - MOM, UP, VOL

Lag	MOM to UP	UP to MOM	MOM to VOL	VOL to MOM
1	0.417317	0.901439	0.566334	0.284092
2	0.390966	0.310021	0.460599	0.569616
3	0.814688	0.207935	0.322965	0.340472
4	0.801098	0.193239	0.971998	0.911317
5	0.564457	0.410175	0.609316	0.111151
6	0.5839	0.160063	0.607837	0.940119
7	0.613149	0.589849	0.627259	0.216869

The results are the same for the control variables, which can be seen in the Appendix. The granger causality tests do not return a p-value less than 0.05 across any of the strategies with all independent variables. There the null hypothesis that X does not granger-cause Y cannot be rejected. In the interest of brevity, these results are not reported.

4.2 VOLATILITY AND MARKET STATE

4.2.1 Univariate Results

Table 6 below shows the results from univariate regressions of the value weighted momentum payoff on market volatility. The only portfolio with a statistically significant coefficient on volatility is the 6-month portfolio. The coefficient on volatility is found to be statistically significant at the 1% level. The sign on the coefficient is negative, indicating that an increase in volatility leads to a decrease in the payoff to the 6-month value weighted momentum strategy.

Table 6 Regression results - value weighted momentum on volatility

	Momentum Payoff (WML)			
	3 Month	6 Month	9 Month	12 Month
Vol	0.158	-1.544***	-0.625	-0.086
	(0.587)	(0.578)	(0.559)	(0.566)
Constant	-0.002	0.021***	0.009	0.004
	(0.007)	(0.007)	(0.007)	(0.007)
N	259	256	253	250
R^2	0.0003	0.027	0.005	0.0001
Adjusted R^2	-0.004	0.023	0.001	-0.004
Residual Std. Error	0.034 (df = 257)	0.034 (df = 254)	0.032 (df = 251)	0.032 (df = 248)
F Statistic	0.073 (df = 1; 257)	7.122*** (df = 1; 254)	1.248 (df = 1; 251)	0.023 (df = 1; 248)

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

The 6-month momentum regression model has an adjusted R-squared of 2.3%, which indicates that volatility explains 2.3% of the variation in the 6-month value weighted momentum payoff. The rest of the adjusted R-squared values are virtually zero, which shows that volatility does not fit the trend of the momentum payoff.

The alpha of the 6-month value weighted model is statistically significant, which means that there is some variation in momentum payoff not explained by volatility. This seems correct given the low adjusted R-squared value. In addition, the f-statistic on the 6-month momentum model is statistically significant at the 5% level, which indicates that the model performs better than an intercept only model.

The table below presents the results of regressions of the equally weighted portfolios on volatility. With the equally weighted portfolios, none of the portfolios have a statistically significant coefficient on volatility. The adjusted R-squared values are, as near as makes no difference, zero. Lastly, none of the f-statistics are statistically significant, therefore, none of the models improve on an intercept only model.

Table 7 Regression results - equally weighted momentum on volatility

	Momentum Payoff (WML)			
	3 Month	6 Month	9 Month	12 Month
Vol	-0.220	-0.491	-0.510	-0.078
	(0.451)	(0.475)	(0.463)	(0.453)
Constant	0.005	0.011^{*}	0.011^{*}	0.008
	(0.006)	(0.006)	(0.006)	(0.005)
N	259	256	253	250
R^2	0.001	0.004	0.005	0.0001
Adjusted R^2	-0.003	0.0003	0.001	-0.004
Residual Std. Error	0.026 (df = 257)	0.028 (df = 254)	0.027 (df = 251)	0.025 (df = 248)
F Statistic	0.237 (df = 1; 257)	1.069 (df = 1; 254)	1.214 (df = 1; 251)	0.030 (df = 1; 248)
Notes:				***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

Market state is not statistically significant at all for any of the strategies, as can be seen in Tables 8 and 9. The R-squared values are next to zero, with the f-statistics being insignificant across the board. This shows that market state does not improve on an intercept only model. Furthermore, market state does not explain any of the variation in the payoff to momentum, irrespective of the construction.

The results show that neither volatility nor market state can explain time varying momentum payoff for 7 out of 8 of the momentum strategies. This indicates that both volatility and volatility in different market states fail to explain time varying momentum profits.

Table 8 Regression results - value weighted momentum on market state

	Momentum Payoff (WML)			
	3 Month	6 Month	9 Month	12 Month
Vol	0.001	0.003	0.001	-0.0002
	(0.005)	(0.005)	(0.005)	(0.005)
Constant	-0.001	0.0004	0.001	0.004
	(0.004)	(0.004)	(0.004)	(0.004)
N	259	256	253	250
R^2	0.0001	0.001	0.0003	0.00001
Adjusted R^2	-0.004	-0.002	-0.004	-0.004
Residual Std. Error	0.034 (df = 257)	0.034 (df = 254)	0.032 (df = 251)	0.032 (df = 248)
F Statistic	0.031 (df = 1; 257)	0.380 (df = 1; 254)	0.072 (df = 1; 251)	0.002 (df = 1; 248)

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Table 9 Regression results - equally weighted momentum on market state

	Momentum Payoff (WML)			
	3 Month	6 Month	9 Month	12 Month
Vol	0.001	0.003	0.001	-0.0002
	(0.005)	(0.005)	(0.005)	(0.005)
Constant	-0.001	0.0004	0.001	0.004
	(0.004)	(0.004)	(0.004)	(0.004)
N	259	256	253	250
R^2	0.0001	0.001	0.0003	0.00001
Adjusted R^2	-0.004	-0.002	-0.004	-0.004
Residual Std. Error	0.034 (df = 257)	0.034 (df = 254)	0.032 (df = 251)	0.032 (df = 248)
F Statistic	0.031 (df = 1; 257)	0.380 (df = 1; 254)	0.072 (df = 1; 251)	0.002 (df = 1; 248)

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.

*Significant at the 10 percent level.

4.2.2 Multivariate Results

Table 10 shows the results of regression outputs of equation 13, with the value weighted momentum portfolios as the response variable. As was the case with the univariate regressions, only the 6-month portfolio yields statistically significant coefficients on the independent variables. Here, both volatility in the up state and volatility in the down state are statistically significant. Furthermore, the coefficients have the hypothesised sign, indicating that an increase in volatility is followed by a decrease in the payoff to momentum.

The coefficient on volatility in the up state is statistically significant at the 5% level while the coefficient on volatility in the down state is statistically significant at the 1% level. The implication, in a similar vein to Wang and Xu (2015), is that volatility in the down state has more explanatory power for time variation in momentum payoff than volatility in the up state.

Table 10 Regression results of value weighted momentum on volatility in the up & down state

	Momentum Payoff (WML)			
	3 Month	6 Month	9 Month	12 Month
Vol+	0.307	-1.382**	-0.525	-0.133
	(0.642)	(0.635)	(0.614)	(0.611)
Vol-	0.088	-1.615***	-0.669	-0.057
	(0.600)	(0.590)	(0.571)	(0.584)
Constant	-0.003	0.020***	0.008	0.005
	(0.007)	(0.007)	(0.007)	(0.007)
N	259	256	253	250
R^2	0.002	0.029	0.006	0.0003
Adjusted R^2	-0.006	0.021	-0.002	-0.008
Residual Std. Error	0.034 (df = 256)	0.034 (df = 253)	0.032 (df = 250)	0.032 (df = 247)
F Statistic	0.202 (df = 2; 256)	3.742** (df = 2; 253)	0.700 (df = 2; 250)	0.033 (df = 2; 247)

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Results of equation 13 with the equally weighted portfolios are just like the univariate regression results. Of the 4 portfolios, neither volatility in the up state nor volatility in the down state are statistically significant. All the f-statistics are insignificant, and the adjusted R-squared values are all close to zero. This means that volatility does not have any association with momentum payoff through time.

Table 11 Regression with equally weighted momentum on volatility in the up & down state

	Momentum Payoff (WML)			
	3 Month	6 Month	9 Month	12 Month
Vol+	-0.469	-0.677	-0.495	0.011
	(0.492)	(0.521)	(0.508)	(0.489)
Vol-	-0.101	-0.409	-0.516	-0.134
	(0.460)	(0.484)	(0.473)	(0.468)
Constant	0.007	0.012^{*}	0.011^{*}	0.007
	(0.006)	(0.006)	(0.006)	(0.006)
N	259	256	253	250
R^2	0.007	0.007	0.005	0.001
Adjusted R^2	-0.001	-0.001	-0.003	-0.007
Residual Std. Error	0.026 (df = 256)	0.028 (df = 253)	0.027 (df = 250)	0.025 (df = 247)
F Statistic	0.907 (df = 2; 256)	0.911 (df = 2; 253)	0.607 (df = 2; 250)	0.136 (df = 2; 247)
Notes:			***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.	

As before, the coefficients on volatility and market state have the correct signs in most of the cases. Additionally, both volatility and volatility in the down state remain statistically significant even in the presence of market state.

Despite including market state and volatility together in one model, the adjusted R-squared does not increase for the 6-month value weighted strategy. In fact, there is a slight decrease in the adjusted R-squared of both models. This shows that the increased complexity of the model has not led to an increase in explanatory power of the variables.

The f-statistics of both regression models are statistically significant. Therefore, volatility does have some informational content for the 6-month value weighted strategy. However, the same cannot be said for the remainder of the strategies as none of the coefficients are statistically significant in neither the univariate nor the multivariate regressions.

The sample period includes three volatile sub periods; the highly volatile 2008-2009 financial crisis, the tech bubble crash and the volatility that followed the Asian financial crisis. Furthermore, volatility was high on the JSE in early 2016. This then suggests that the lack of statistical significance is not for a lack of highly volatile periods.

Given that there are a sufficient number of high volatility observations, the results are in stark contrast with the results of Wang and Xu (2015). The findings of Wang and Xu (2015) reveal that in the US market, volatility and market state work strongly together to explain momentum profits through time.

Figure 5 below illustrates why volatility is not statistically significant for 7 out of the 8 portfolios. The graph plots the 9-month value weighted momentum payoff in a month against the lagged 12-month volatility in that month. A linear model has been fitted through the points. The fitted model is virtually a straight horizontal line, showing that there is hardly any relationship between momentum and volatility.

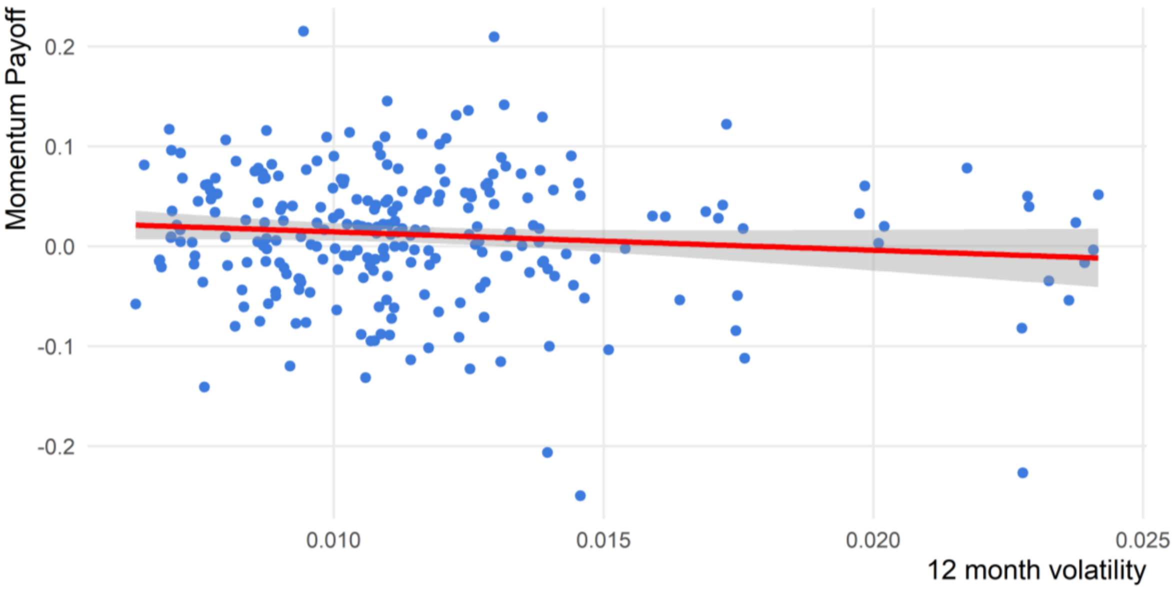

Figure 5 Linear model of momentum and volatility - 9-month value weighted

4.3 VOLATILITY RELATED MEASURES

In this chapter, four measures that are closely linked to volatility are used in an attempt to improve on the results. The four measures are downside risk, return dispersion, FEARS index and the SAVI. The results on all four are reported in consecutive sub chapters.

4.3.1 Volatility and Downside Risk (Semi Deviation)

Downside risk is related to volatility and hence semi deviation is used in place of volatility to observe if downside risk can explain time varying momentum better than volatility.

Table 12 presents results from the equally weighted momentum strategies. Previously, volatility was not statistically significant on any of these strategies. However, here the 6-month portfolio has a negative and statistically significant coefficient on semi deviation, which is significant at the 5% level. This remains true even when semi deviation is included with market state.

Table 12 Semi deviation - equally weighted

	Momentum Payoff (WML)			
	3 Month	6 Month	9 Month	12 Month
SEMI	-0.602	-0.946**	-0.654	0.109
	(0.378)	(0.398)	(0.415)	(0.400)
Constant	0.007**	0.011***	0.010***	0.006*
	(0.003)	(0.003)	(0.003)	(0.003)
N	259	256	253	250
R^2	0.010	0.022	0.010	0.0003
Adjusted R^2	0.006	0.018	0.006	-0.004
Residual Std. Error	0.026 (df = 257)	0.027 (df = 254)	0.025 (df = 251)	0.025 (df = 248)
F Statistic	2.534 (df = 1; 257)	5.652** (df = 1; 254)	2.486 (df = 1; 251)	0.074** (df = 1; 248)
Notes:				***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

Regressions with 6-month value weighted strategy also produces a statistically significant coefficient on semi deviation, as can be seen in Table 13 below. The coefficients from both the univariate model and the multivariate model are statistically significant at the 1% level. There is an improvement in the adjusted R-squared of the models, with 3.8% for the model with semi deviation only and 3.6% for the model with semi deviation and market state.

Table 13 Semi deviation - value weighted

	Momentum Payoff (WML)			
	3 Month	6 Month	9 Month	12 Month
SEMI	-0.411	-1.436***	-0.541	-0.700

	(0.487)	(0.482)	(0.496)	(0.887)
Constant	0.003	0.013***	0.006	0.021***
	(0.004)	(0.004)	(0.004)	(0.007)
N	259	256	253	250
R^2	0.003	0.034	0.005	0.003
Adjusted R^2	-0.001	0.030	0.001	-0.002
Residual Std. Error	0.034 (df = 257)	0.034 (df = 254)	0.032 (df = 251)	0.056 (df = 248)
F Statistic	0.710 (df = 1; 257)	8.876*** (df = 1; 254)	1.186 (df = 1; 251)	0.623 (df = 1; 248)

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Overall semi deviation performs slightly better, but ultimately time variation in momentum profits is still unexplained on 6 out of 8 momentum strategies.

4.3.2 Volatility and Implied Volatility

Volatility and implied volatility are related to each other. Implied volatility is a forward-looking measure, derived from options prices by solving for the volatility in the Black-Scholes-Merton model. The South African Volatility Index (SAVI) is built from the option implied volatilities obtained from Top-40 options (Johannesburg Stock Exchange, n.d.).

However, this approach is relatively new in South Africa and as such the SAVI only has data from 2007 onwards as that was when the SAVI was introduced by the JSE. Market volatility has a correlation of 0.86 with the SAVI. The rationale for including implied volatility is similar to that of the sentiment index. Implied volatilities are a forward-looking measure of stock market volatility. If the SAVI increases, then market volatility is likely to increase. For this reason, the SAVI is used in place of volatility.

The SAVI does not perform better than volatility in the regressions as not a single coefficient is statistically significant in regressions for any of the strategies. This includes the 6-month value weighted strategy, which previously had a statistically significant coefficient on volatility in the univariate regressions

Table 14 shows the results of regressions with the value weighted portfolios as the response variable. The adjusted R-squared values are effectively zero for all the regression models. None of the f-statistics are statistically significant, showing that the model offers no improvement over a simple constant only model.

Table 15 shows the results of regressions with equally weighted momentum payoff as the dependent variables. The outcome is on par with the value weighted portfolio results. Note that in this case the number of observations, *N*, is the same for all portfolios because observations for the SAVI only start in 2007.

Table 14 Regression results of value weighted portfolios on SAVI

	Momentum Payoff (WML)			
	3 Month	6 Month	9 Month	12 Month
SAVI	0.0003	-0.0004	-0.0004	-0.001
	(0.0004)	(0.0004)	(0.0004)	(0.001)
Constant	-0.006	0.012	0.011	0.034**
	(0.009)	(0.010)	(0.009)	(0.016)
N	149	149	149	149
R^2	0.003	0.006	0.007	0.017
Adjusted R^2	-0.004	-0.0004	0.001	0.010
Residual Std. Error (df = 147)	0.032	0.035	0.032	0.056
F Statistic (df = 1; 147)	0.412	0.937	1.086	2.534

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Table 15 Regression results of equally weighted portfolios on SAVI

	Momentum Payoff (WML)			
	3 Month	6 Month	9 Month	12 Month
SAVI	0.001	-0.0004	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Constant	-0.012	0.016	0.037*	0.034**
	(0.015)	(0.015)	(0.015)	(0.016)
N	149	149	149	149
R^2	0.009	0.002	0.007	0.011
Adjusted R^2	0.002	-0.005	0.002	0.007
Residual Std. Error (df = 147)	0.053	0.055	0.054	0.056
F Statistic (df = 1; 147)	1.339	0.287	1.043	2.534

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.

*Significant at the 10 percent level.

4.4 VOLATILITY AND OTHER CONTROL VARIABLES

4.4.1 Volatility and Return Dispersion

The 6-month value weighted strategy was the only strategy with a statistically significant coefficient on either volatility or volatility in the down state. This result remains true when market state is included with volatility. Volatility is still statistically significant at the 5% level for the 6-month portfolio when return dispersion is included. However, when the macroeconomic variables are included, volatility fails to retain statistical significance as it is no longer statistically significant at any level. The same is also true for volatility in the down state.

Table 16 Momentum and return dispersion – value weighted momentum

	Momentum Payoff (WML)			
	3 Month	6 Month	9 Month	12 Month
VOL	-0.304	-1.289**	-0.558	0.067
	(0.643)	(0.634)	(0.607)	(0.602)
RD	0.249*	-0.142	-0.043	-0.120
	(0.145)	(0.146)	(0.150)	(0.158)
Constant	-0.007	0.024***	0.010	0.008
	(0.008)	(0.008)	(0.008)	(0.008)
N	259	256	253	250
R^2	0.012	0.031	0.005	0.002
Adjusted R^2	0.004	0.023	-0.003	-0.006
Residual Std. Error	0.034 (df = 256)	0.034 (df = 253)	0.032 (df = 250)	0.032 (df = 247)
F Statistic	1.519 (df = 2; 256)	4.036** (df = 2; 253)	0.662 (df = 2; 250)	0.299 (df = 2; 247)

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Table 17 Momentum and return dispersion - equally weighted portfolios

	Momentum Payoff (WML)			
	3 Month	6 Month	9 Month	12 Month
VOL	-0.185	-0.987	-1.565	-1.482
	(0.998)	(1.081)	(1.051)	(1.066)

RD	0.170	-0.107	-0.151	-0.179
	(0.225)	(0.248)	(0.260)	(0.280)
Constant	0.001	0.028**	0.039***	0.040***
	(0.012)	(0.013)	(0.013)	(0.014)
N	259	256	253	250
R^2	0.002	0.006	0.015	0.013
Adjusted R^2	-0.005	-0.002	0.007	0.005
Residual Std. Error	0.053 (df = 256)	0.058 (df = 253)	0.056 (df = 250)	0.056 (df = 247)
F Statistic	0.298 (df = 2; 256)	0.807 (df = 2; 253)	1.898 (df = 2; 250)	1.656 (df = 2; 247)

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Interestingly, both 3-month strategies produce statistically significant coefficients on return dispersion and all the macroeconomic variables but not on volatility (see Tables 18 and 19). However, neither return dispersion nor macroeconomic variables have explanatory power for momentum on a univariate basis.

Table 18 Volatility, return dispersion and macroeconomic variables - value weighted portfolios

	Momentum Payoff (WML)			
	3 Month	6 Month	9 Month	12 Month
VOL	0.188	-0.829	-0.603	0.090
	(0.719)	(0.716)	(0.689)	(0.678)
RD	0.459**	-0.067	0.023	-0.056
	(0.179)	(0.181)	(0.179)	(0.182)
YLD	-3.754**	-1.185	-0.973	-0.886
	(1.573)	(1.576)	(1.545)	(1.570)
TERM	-4.641**	0.429	-1.588	-0.059
	(2.160)	(2.157)	(2.073)	(2.054)
DIV	-0.008**	-0.004	0.001	0.003
	(0.004)	(0.004)	(0.004)	(0.004)
Constant	0.032*	0.034**	0.013	0.001
	(0.017)	(0.017)	(0.016)	(0.016)
N	259	256	253	250
R^2	0.041	0.039	0.010	0.009
Adjusted R^2	0.022	0.020	-0.011	-0.012

Residual Std. Error	0.034 (df = 253)	0.034 (df = 250)	0.032 (df = 247)	0.032 (df = 244)
F Statistic	2.184* (df = 5; 253)	2.040* (df = 5; 250)	0.476 (df = 5; 247)	0.434 (df = 5; 244)
Notes:				***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

Table 19 Volatility, return dispersion, macroeconomic terms - equally weighted portfolios

	Momentum Payoff (WML)			
	3 Month	6 Month	9 Month	12 Month
VOL	0.195	-0.655	-1.599	-1.235
	(1.116)	(1.224)	(1.192)	(1.204)
RD	0.477*	-0.010	-0.268	-0.203
	(0.278)	(0.310)	(0.310)	(0.324)
YLD	-5.462**	-1.436	1.809	0.081
	(2.442)	(2.693)	(2.673)	(2.787)
TERM	-8.525**	-0.437	2.459	0.671
	(3.353)	(3.687)	(3.587)	(3.647)
DIV	-0.009**	-0.002	-0.001	-0.004
	(0.006)	(0.007)	(0.007)	(0.007)
Constant	0.056**	0.037	0.031	0.050*
	(0.026)	(0.029)	(0.028)	(0.029)
N	259	256	253	250
R^2	0.031	0.008	0.018	0.016
Adjusted R^2	0.012	-0.012	-0.002	-0.004
Residual Std. Error	0.053 (df = 253)	0.058 (df = 250)	0.056 (df = 247)	0.057 (df = 244)
F Statistic	1.628 (df = 5; 253)	0.396 (df = 5; 250)	0.907 (df = 5; 247)	0.788 (df = 5; 244)
Notes:				***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

4.4.2 Volatility and Sentiment (FEARS Index)

As mentioned earlier in Chapter 3, the FEARS index here replaces the Baker and Wurgler (2006) sentiment index utilised by Wang and Xu (2015). The rationale given by Wang and Xu (2015) for including a sentiment index is that sentiment lags market conditions. If sentiment shows investors to be fearful, then one can expect volatility to increase in the market soon afterwards. Therefore, including a sentiment index with volatility may improve the informational content of the model.

Across all strategies, including the FEARS index does not lead to increased explanatory power of volatility. The 6-month value weighted strategy had both volatility and volatility in the down state as statistically significant in the univariate and multivariate regressions. When included with the FEARS index, neither volatility nor volatility in the down state are statistically significant. This shows that the results of volatility on the 6-month value weighted strategy are not robust.

Table 20 Volatility and sentiment - value weighted portfolios

	Momentum Payoff (WML)			
	3 Month	6 Month	9 Month	12 Month
VOL	0.385	-0.223	-0.321	0.378
	(0.789)	(0.846)	(0.836)	(0.729)
FEARS	0.006	0.003	-0.007	-0.002
	(0.010)	(0.011)	(0.011)	(0.009)
YLD	-5.370	3.525	0.097	-0.978
	(4.599)	(4.929)	(4.875)	(4.250)
TERM	-0.785	5.255	1.005	-2.187
	(4.217)	(4.520)	(4.470)	(3.898)
DIV	0.009*	0.005	0.010*	0.011**
	(0.006)	(0.006)	(0.006)	(0.005)
Constant	-0.017	-0.042	-0.029	-0.018
	(0.032)	(0.034)	(0.034)	(0.029)
N	128	128	128	128
R^2	0.076	0.020	0.031	0.054
Adjusted R^2	0.038	-0.020	-0.009	0.015
Residual Std. Error (df = 122)	0.028	0.030	0.030	0.026
F Statistic (df = 5; 122)	1.997*	0.505	0.768	1.387

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

It can be concluded that the FEARS index does not include any informational content over and above volatility and market state. However, note that the FEARS index is constructed using Googles search volume index, which only begins in 2004. Furthermore, the data is thin on the search volume in the earlier years.

For this reason, the regressions are performed using only data from 2007. This means that there are only two periods of high volatility for the regressions; the 2008-2009 financial crisis and the few months of early 2016.

Table 21 Volatility and sentiment - equally weighted portfolios

	Momentum Payoff (WML)			
	3 Month	6 Month	9 Month	12 Month
VOL	0.385	-0.223	-0.321	0.378
	(0.789)	(0.846)	(0.836)	(0.729)
FEARS	0.006	0.003	-0.007	-0.002
	(0.010)	(0.011)	(0.011)	(0.009)
YLD	-5.370	3.525	0.097	-0.978
	(4.599)	(4.929)	(4.875)	(4.250)
TERM	-0.785	5.255	1.005	-2.187
	(4.217)	(4.520)	(4.470)	(3.898)
DIV	0.009*	0.005	0.010*	0.011**
	(0.006)	(0.006)	(0.006)	(0.005)
Constant	-0.017	-0.042	-0.029	-0.018
	(0.032)	(0.034)	(0.034)	(0.029)
N	128	128	128	128
R^2	0.076	0.020	0.031	0.054
Adjusted R^2	0.038	-0.020	-0.009	0.015
Residual Std. Error (df = 122)	0.028	0.030	0.030	0.026
F Statistic (df = 5; 122)	1.997*	0.505	0.768	1.387

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

4.5 VOLATILITY AND DEFAULT RISK

In Chapter 4.2, it was shown that both volatility and volatility in the down state are statistically significant at the 5% level for the 6-month value weighted strategy. This was the only portfolio in which volatility was statistically significant. Further tests in Chapter 4.2.2 revealed that volatility and volatility in the down state do remain statistically significant at the 5% level in multivariate regressions with market state. The main strategy of interest here is the 6-month value weighted strategy. This is because volatility and volatility in the down state were significant on only this strategy.

In this chapter, volatility is included with default probabilities, macroeconomic variables and market state. Default probabilities are calculated using Merton (1974) credit risk model, as described in the methodology chapter of this study.

Table 22 shows the results of the value weighted strategies. Volatility is no longer statistically significant for the 6-month portfolio. However, default risk is statistically significant at the 5% level. This shows that in the presence of default risk, volatility does not retain explanatory power for momentum generated by a 6-month value weighted strategy.

Interestingly, default risk is also statistically significant on the 6-month equally weighted strategies and both 9-month strategies. Volatility is not statistically significant in any of these regressions and was also not significant in the main regressions from Chapter 4.2.

Table 22 Momentum and default risk - value weighted portfolios

	Momentum Payoff (WML)			
	3 Month	6 Month	9 Month	12 Month
VOL+	0.352	-0.819	-0.437	0.176
	(0.734)	(0.716)	(0.688)	(0.681)
VOL-	0.395	-0.539	-0.654	0.172
	(0.816)	(0.798)	(0.776)	(0.765)
DEF	0.107	-0.488**	-0.414**	-0.410
	(0.229)	(0.240)	(0.243)	(0.264)
YLD	-1.806	-0.226	0.436	-0.356
	(1.529)	(1.498)	(1.477)	(1.470)
TERM	-3.376	1.088	-0.832	0.585
	(2.151)	(2.111)	(2.060)	(2.052)
DIV	-0.008*	-0.002	0.005	0.007
	(0.005)	(0.005)	(0.005)	(0.005)
Constant	0.031	0.032*	0.002	-0.004
	(0.019)	(0.019)	(0.018)	(0.018)
N	259	256	253	250
R^2	0.017	0.055	0.054	0.018
Adjusted R^2	-0.006	0.032	0.031	-0.006
Residual Std. Error	0.034 (df = 252)	0.034 (df = 249)	0.032 (df = 246)	0.032 (df = 243)
F Statistic	0.748 (df = 6; 252)	2.406** (df = 6; 249)	2.996** (df = 6; 246)	0.757 (df = 6; 243)
Notes:			***Significant at the 1 percent level.	

**Significant at the 5 percent level.
*Significant at the 10 percent level.

Table 23 Momentum and default risk - equally weighted portfolios

	Momentum Payoff (WML)			
	3 Month	6 Month	9 Month	12 Month
VOL+	0.246	-0.646	-1.398	-0.966
	(1.129)	(1.228)	(1.191)	(1.206)
VOL-	0.979	-0.137	-1.977	-1.835
	(1.256)	(1.368)	(1.341)	(1.357)
DEF	-0.033	-0.619**	-0.774**	-0.641
	(0.353)	(0.412)	(0.419)	(0.469)
YLD	-3.493	0.035	3.175	1.021
	(2.353)	(2.568)	(2.554)	(2.605)
TERM	-6.828**	0.670	2.930	1.061
	(3.311)	(3.620)	(3.563)	(3.637)
DIV	-0.011	-0.0004	0.008	0.005
	(0.007)	(0.008)	(0.008)	(0.008)
Constant	0.067**	0.037	0.008	0.027
	(0.030)	(0.033)	(0.032)	(0.032)
N	259	256	253	250
R^2	0.024	0.058	0.053	0.028
Adjusted R^2	0.001	0.036	0.034	0.004
Residual Std. Error	0.053 (df = 252)	0.058 (df = 249)	0.056 (df = 246)	0.056 (df = 243)
F Statistic	1.026 (df = 6; 252)	2.742** (df = 6; 249)	2.413** (df = 6; 246)	1.180 (df = 6; 243)

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Of all the regressions performed thus far, a statistically significant coefficient on a control variable in the presence of volatility has not yielded a statistically significant coefficient on the control variable in univariate regressions. Remarkably, this is not the case with default risk as the three strategies where default risk was significant with volatility and macroeconomic variables, are the same three strategies where default risk is statistically significant in univariate regressions.

Table 24 below shows the results of univariate regressions with momentum as the dependent variable and default risk as the independent variable. The strategies that returned statistically significant coefficients on default risk are both 6-month momentum portfolios and the 9-month equally weighted portfolio. The coefficients on all three are negative, which means that when default risk increases, momentum payoff of these three strategies decreases.

Table 24 Default risk and momentum payoff

	6-month momentum (equally weighted)	6-month momentum (value weighted)	9-month momentum (equally weighted)
DEF	-0.395***	-0.617***	
	(0.148)	(0.181)	
DEF			-0.401***
			(0.154)
Constant	0.017***	0.021***	0.017***
	(0.005)	(0.006)	(0.005)
N	256	256	253
R^2	0.027	0.044	0.026
Adjusted R^2	0.024	0.040	0.022
Residual Std. Error	0.027 (df = 254)	0.034 (df = 254)	0.026 (df = 251)
F Statistic	7.151*** (df = 1; 254)	11.682*** (df = 1; 254)	6.763*** (df = 1; 251)
Notes:			***Significant at the 1 percent level.
			**Significant at the 5 percent level.
			*Significant at the 10 percent level.

Figure 6 plots default risk as well as the drawdowns of the winner and loser portfolios of the 9-month equally weighted momentum strategy through time. The graph shows why default risk is significant. Default risk starts off high in 1998 following the Asian financial crisis. A rather surprising fact is that the magnitude of negative market returns of the JSE is larger following the Asian financial crisis than the negative market returns during the 2008 financial crisis. This potentially contributes to the abnormally high probability of default in the late 1990s.

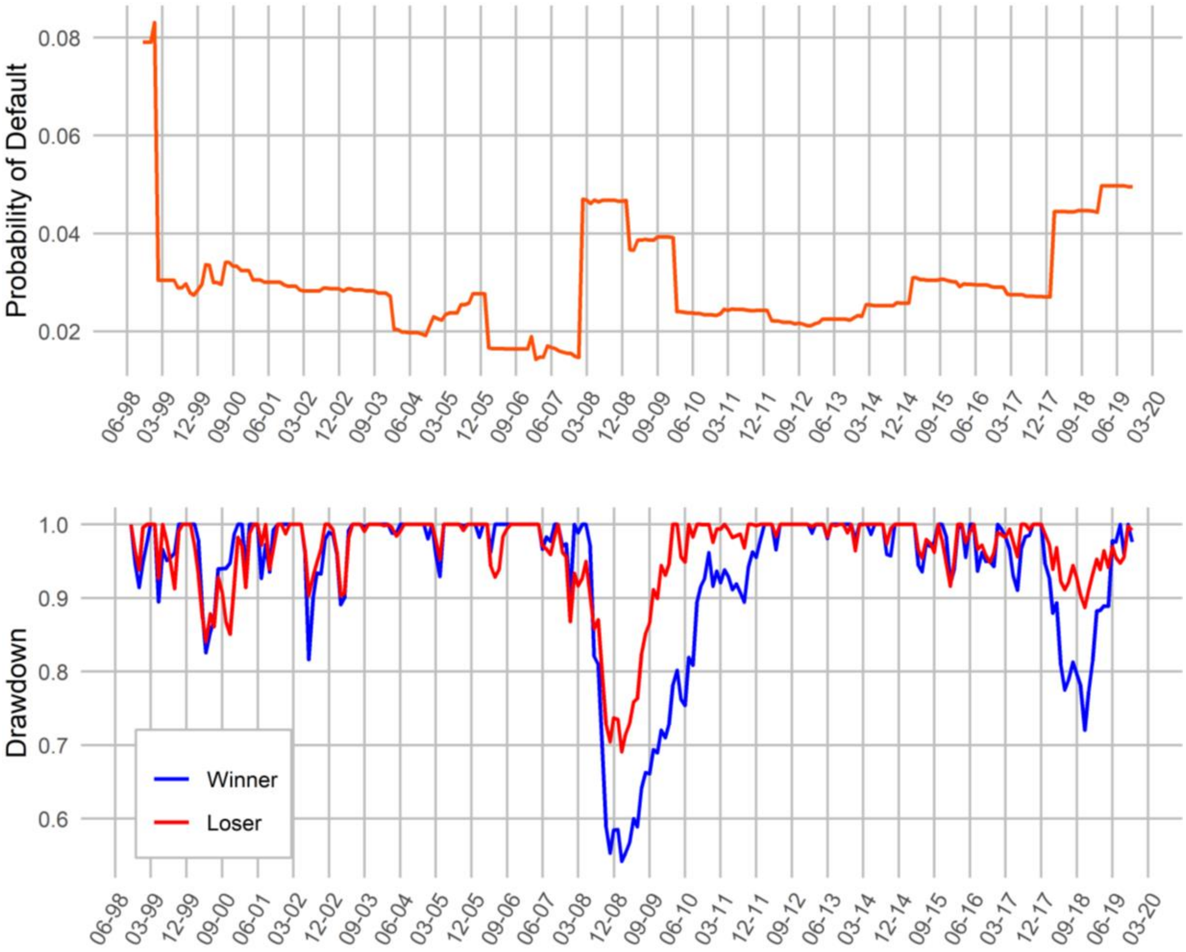

Figure 6 9-month equally weighted momentum and probability of default

4.6 MOMENTUM AND SIZE

The overall conclusion so far is that both volatility and market do not have significant explanatory power for momentum on the JSE. To determine if this result is robust, size balanced momentum portfolios are considered as well. There are two size portfolios, large and small stocks. The large stocks are the shares that are in the top 50 shares by market capitalisation. The rest of the shares are classified as small. Momentum is then constructed in the same manner as before on both size portfolios.

The results show that volatility and market state are not statistically significant on large stocks on all but one of the eight portfolios. Even the 6-month value weighted portfolio, which previously had a statistically significant coefficient on volatility and volatility in the down state, did not have a statistically significant coefficient. The one exception was the 12-month equally weighted large stock momentum portfolio.

Table 25 shows the results of univariate regressions of the 6-month equally weighted portfolio formed on small stocks on volatility, volatility in the up and down state and market state. In this case, both volatility and volatility in the down state are statistically significant at the 5% level. Both coefficients are negative, which shows that an increase in volatility leads to a decrease in the payoff to momentum when it is constructed on smalls stocks with a 6-month lookback period. Volatility in the up state is not statistically significant, which matches the results of Wang and Xu (2015), who find that volatility in the down state has stronger explanatory power than both volatility in the up state and overall volatility. This is the only momentum portfolio formed on large stocks to return statistically significant coefficients on either volatility, volatility in up and down market states or market state.

Table 25 also shows that market state has explanatory power for 6-month momentum formed on small stocks as the coefficient is statistically significant at the 5% level. Furthermore, the coefficient on market state has the hypothesised relationship, with a positive sign on the coefficient. This shows that a positive change in market state leads to an increase in the payoff to momentum.

Table 25 Volatility, Market State Univariate - 6-month equally weighted on small stocks

	Momentum Payoff		
	(1)	(2)	(3)
Vol	-1.839**		
	(0.782)		
Vol+		-1.208	
		(1.010)	
Vol-		-1.777**	
		(0.784)	
MKT			0.015**
			(0.007)
Constant	0.029***	0.024**	-0.004
	(0.010)	(0.011)	(0.006)
N	256	256	256
R^2	0.021	0.025	0.016
Adjusted R^2	0.017	0.017	0.013
Residual Std. Error	0.046 (df = 254)	0.046 (df = 253)	0.046 (df = 254)
F Statistic	5.535** (df = 1; 254)	3.255** (df = 2; 253)	4.253** (df = 1; 254)
Notes:			***Significant at the 1 percent level.
			**Significant at the 5 percent level.

*Significant at the 10 percent level.

Although volatility, volatility in the down state and market state are statistically significant in univariate regressions, none of the three remain statistically significant in multivariate regressions. Table 26 below shows results from the multivariate regressions of the 6-month value weighted small stock momentum portfolio. This shows that the results of volatility and market state are not robust.

Table 26 Volatility, Market state multivariate - 6-month equally weighted on small stocks

	Momentum Payoff	
	(1)	(2)
MKT	0.009	0.015
	(0.008)	(0.024)
Vol	-1.397	
	(0.872)	
Vol+		-1.625
		(1.206)
Vol-		-1.146
		(1.267)
Constant	0.017	0.013
	(0.014)	(0.020)
N	256	256
R^2	0.026	0.027
Adjusted R^2	0.019	0.015
Residual Std. Error	0.046 (df = 253)	0.046 (df = 252)
F Statistic	3.424^{**} (df = 2; 253)	2.299^{*} (df = 3; 252)
Notes:	***Significant at the 1 percent level.	
	**Significant at the 5 percent level.	
	*Significant at the 10 percent level.	

Table 27 below presents the results of the regressions with the 9-month equally weighted portfolio return as the response variable. Here, volatility is statistically significant at the 5% level. This is also true for volatility in the down state. Unlike the 6-month equally weighted strategy, market state is not statistically significant.

Table 27 Volatility, Market State - 9-month equally weighted on small stocks

	Momentum Payoff		
	(1)	(2)	(3)
Vol	-1.731**		
	(0.788)		
Vol+		-1.505	
		(1.006)	
Vol-		-1.717**	
		(0.790)	
MKT			0.009
			(0.007)
Constant	0.031***	0.029***	0.004
	(0.010)	(0.011)	(0.007)
N	253	253	253
R^2	0.019	0.019	0.006
Adjusted R^2	0.015	0.012	0.003
Residual Std. Error	0.045 (df = 251)	0.045 (df = 250)	0.046 (df = 251)
F Statistic	4.830** (df = 1; 251)	2.473* (df = 2; 250)	1.632 (df = 1; 251)
Notes:			***Significant at the 1 percent level.
			**Significant at the 5 percent level.
			*Significant at the 10 percent level.

Table 28 shows the results from the multivariate regression of the same strategy. With volatility and market state included together, volatility is not statistically significant at the 5% level and volatility in the down state is also insignificant. This shows that the results of volatility and market state on a univariate basis are not robust.

Table 28 Volatility, Market state - 9-month equally weighted on small stocks

	Momentum Payoff	
	(1)	(2)
MKT	0.003	0.003
	(0.008)	(0.024)
Vol	-1.587*	
	(0.871)	
Vol+		-1.598
		(1.201)
Vol-		-1.576
		(1.271)
Constant	0.027*	0.027

	(0.014)	(0.020)
N	253	253
R^2	0.019	0.019
Adjusted R^2	0.012	0.008
Residual Std. Error	0.045 (df = 250)	0.046 (df = 249)
F Statistic	2.483* (df = 2; 250)	1.649 (df = 3; 249)
Notes:		***Significant at the 1 percent level.
		**Significant at the 5 percent level.
		*Significant at the 10 percent level.

Table 29 below reports the results from the 12-month small capitalisation equally weighted momentum strategy. The results show that market state by itself is statistically significant at the 5% level. The coefficient market state is positive, which signifies momentum payoff changes through time is positively associated with market state. If market state is negative, momentum profits decrease on the 12-month small capitalisation equally weighted momentum strategy. Volatility is not statistically significant at the 5% level, neither is volatility in the up state nor volatility in the down state.

Table 29 Volatility, market state univariate - 12-month equally weighted on small stocks

	Momentum Payoff		
	(1)	(2)	(3)
Vol	-1.204		
	(0.802)		
Vol+		-0.097	
		(1.028)	
Vol-		-1.105	
		(0.801)	
MKT			0.015**
			(0.007)
Constant	0.025***	0.015	-0.001
	(0.010)	(0.011)	(0.006)
N	250	250	250
R^2	0.009	0.021	0.018
Adjusted R^2	0.005	0.013	0.014
Residual Std. Error	0.045 (df = 248)	0.045 (df = 247)	0.045 (df = 248)
F Statistic	2.254 (df = 1; 248)	2.599* (df = 2; 247)	4.559** (df = 1; 248)
Notes:			***Significant at the 1 percent level.
			**Significant at the 5 percent level.

*Significant at the 10 percent level.

Reported in Table 30 below are the multivariate results of the same strategy in Table 14. Although market state is statistically significant in univariate regressions, market state is not statistically significant with volatility and volatility in the up state and volatility in the down state, yet again showing the lack of robustness in the univariate results.

Table 30 Volatility and market state multivariate - 12-month equally weighted on small stocks

	Momentum Payoff	
	(1)	(2)
MKT	0.013	0.002
	(0.008)	(0.024)
Vol	-0.579	
	(0.885)	
Vol+		-0.166
		(1.242)
Vol-		-1.009
		(1.265)
Constant	0.007	0.014
	(0.014)	(0.020)
N	250	250
R^2	0.020	0.021
Adjusted R^2	0.012	0.009
Residual Std. Error	0.045 (df = 247)	0.045 (df = 246)
F Statistic	2.488* (df = 2; 247)	1.729 (df = 3; 246)
Notes:	***Significant at the 1 percent level.	
	**Significant at the 5 percent level.	
	*Significant at the 10 percent level.	

The results in Table 31 are from regressions of the 9-month value weighted momentum portfolio formed on small stocks. On this strategy, volatility is not statistically significant. Market state is statistically significant at 5% level with a positive coefficient, which matches the hypothesised positive relationship between market states and the payoff to momentum. However, market state is not significant when included with volatility and volatility in the up state and volatility in the down state.

Table 31 Volatility, market state – 9-month value weighted on small stocks

	Momentum Payoff		
	(1)	(2)	(3)
Vol	-1.173		
	(1.010)		
Vol+		-0.045	
		(1.285)	
Vol-		-1.100	
		(1.010)	
MKT			0.020^{**}
			(0.009)
Constant	0.017	0.007	-0.012
	(0.012)	(0.014)	(0.008)
N	253	253	253
R^2	0.005	0.013	0.018
Adjusted R^2	0.001	0.005	0.015
Residual Std. Error	0.058 (df = 251)	0.058 (df = 250)	0.058 (df = 251)
F Statistic	1.347 (df = 1; 251)	1.679 (df = 2; 250)	4.719^{**} (df = 1; 251)
Notes:			***Significant at the 1 percent level.
			**Significant at the 5 percent level.
			*Significant at the 10 percent level.

4.7 ALTERNATIVE DEFINITIONS OF MARKET STATE

The regressions thus far have used the lagged 12-month daily standard deviation of market returns. Using that definition, only the 6-month value weighted portfolio had a statistically significant coefficient on volatility. The 6-month value weighted portfolio also had a statistically significant coefficient on volatility in the down state. These results were not robust as none of the coefficients remained statistically significant in multivariate regressions with default risk, sentiment and macroeconomic variables.

4.7.1 <u>6-month lagged market volatility</u>

This sub-chapter reports results of regressions using lagged 6-month daily standard deviation of market returns. Note that market state in this sub chapter is still based on the lagged 6-month market return. Table 32 shows the results of univariate regressions of momentum payoff on volatility, market state and volatility in up and down market states. The coefficients on volatility and volatility in the down are both statistically significant at the 1% level. The signs on the coefficients are negative, which is indicative of that an increase in volatility and volatility in the down state leading to a decrease in the payoff to the 6-month value weighted momentum strategy. This in agreement with Wang and Xu (2015) results. In addition, volatility in the up state being statistically significant at the 5% level matches Wang and Xu (2015) finding that volatility in the down state has more explanatory power for momentum payoff than volatility in the up state.

The adjusted R-squared values are 3% for the volatility model and 2.7% for the model with up market and down market volatilities. The model on market state model has an adjusted R-square value of -0.2%, which shows that market state does not have any explanatory power for momentum. The f-statistic on the volatility model is statically significant at the 1% level whilst the f-statistic on the up market and down market volatilities is significant at the 5% level.

Table 32 Market state and 6-month volatility univariate – 6-month value weighted

	Momentum Payoff		
	(1)	(2)	(3)
Vol	-1.540^{***}		
	(0.514)		
Vol+		-1.581^{**}	
		(0.656)	
Vol-		-1.541^{***}	
		(0.515)	
MKT			0.003
			(0.005)
Constant	0.020^{***}	0.020^{***}	0.0004
	(0.006)	(0.007)	(0.004)
N	256	256	256
R^2	0.034	0.034	0.001
Adjusted R^2	0.030	0.027	-0.002
Residual Std. Error	0.034 (df = 254)	0.034 (df = 253)	0.034 (df = 254)
F Statistic	8.985^{***} (df = 1; 254)	4.480^{**} (df = 2; 253)	0.380 (df = 1; 254)
Notes:			***Significant at the 1 percent level.
			**Significant at the 5 percent level.
			*Significant at the 10 percent level.

Table 33 below shows the results from the multivariate regressions. When included together with market state, both volatility and volatility in the down state remain statistically significant at the 1% level of significance. This shows that the results of 6-month volatility are robust on the 6-month value weighted strategy.

Table 33 Market state and 6-month volatility multivariate – 6-month value weighted

	Momentum Payoff	
	(1)	(2)
MKT	-0.003	-0.019
	(0.005)	(0.014)
Vol	-1.657***	
	(0.556)	
Vol+		-0.968
		(0.810)
Vol-		-2.269***
		(0.764)
Constant	0.024***	0.032***
	(0.009)	(0.011)
N	256	256
R^2	0.035	0.041
Adjusted R^2	0.028	0.029
Residual Std. Error	0.034 (df = 253)	0.034 (df = 252)
F Statistic	4.632** (df = 2; 253)	3.548** (df = 3; 252)
Notes:		***Significant at the 1 percent level.
		**Significant at the 5 percent level.
		*Significant at the 10 percent level.

4.7.2 36-month lagged market state

In this chapter, market state is based on the lagged 36-month market return. This is the original definition used by Cooper *et al*., (2004). Although Wang and Xu (2015) changed it to 6-months after finding that the market was rarely in down states with this definition, Wang and Xu (2015) still use this definition in robustness tests. This definition of market state is employed here for the same reason. Naturally, volatility in the up state and volatility in the down state will change as well, as both are defined using market state. This chapter uses the lagged 12-month daily standard deviation of market returns to define market volatility.

With the previous definition of market state, the coefficient on market state was not statistically significant on any of the main portfolios. Considering that market state uses a longer window, and therefore hardy ever changes (number of down market states is just 1%), it is not surprising that market state is not statistically with this definition as well.

The 6-month strategy had a statistically significant coefficient on both volatility and volatility in the up state. Since the definition of volatility is the same, the result on volatility in univariate regressions remain the same, and this is the case on the other strategies. The variable of interest here is volatility in the down state. As it was before, the coefficient is statistically significant at the 5% level. However, it should be noted that there aren't enough observations of down months with this definition to draw meaningful conclusions. The results of this regression can be seen in Table 34 below.

Table 34 36-month market state univariate - 6-month value weighted

	Momentum Payoff		
	(1)	(2)	(3)
Vol	-1.544^{***}		
	(0.578)		
Vol+		-1.166	
		(0.748)	
Vol-		-1.506^{**}	
		(0.581)	
MKT			0.009
			(0.005)
Constant	0.021^{***}	0.017^{**}	-0.004
	(0.007)	(0.008)	(0.005)
N	256	256	256
R^2	0.027	0.030	0.010
Adjusted R^2	0.023	0.022	0.006
Residual Std. Error	0.034 (df = 254)	0.034 (df = 253)	0.034 (df = 254)
F Statistic	7.122^{***} (df = 1; 254)	3.873^{**} (df = 2; 253)	2.663 (df = 1; 254)
Notes:			***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

The results of the rest of the strategies do not return a statistically significant coefficient on market state or volatility in the up and down state. Therefore, the results on these strategies are not reported.

4.8 REFINED MOMENTUM

Wang and Xu (2015) create a “refined” momentum strategy that uses volatility to enhance the payoff to momentum. The trading rule behind the strategy is simple, if a month is classified as a month of high volatility, then the momentum strategy is reversed. That means an investor would be long the loser portfolio and short the loser portfolio. Wang and Xu (2015) assign the label of high volatility to a month if daily standard deviation of market returns in the last twelve months is higher than daily standard deviation of market returns in the last thirty-six months.

Wang and Xu (2015) refined momentum strategy outperforms the standard momentum strategy by a huge margin. The return to the refined momentum strategy is 299.85%, while the return on the standard momentum strategy is 22.61%. This chapter implements the refined momentum strategy on the JSE to test if the refined momentum strategy outperforms the standard momentum strategy. As mentioned earlier, the JSE is different to the NYSE, as the JSE is characterised by market segmentation. Therefore, this study serves as an out of sample test of the refined momentum strategy proposed by Wang and Xu (2015).

Figure 7 shows the cumulative performance, drawdowns and monthly returns of the refined momentum strategy and the standard momentum strategy. The lookback period is 6-months, employing a value weighting scheme. The standard momentum strategy is simply winner minus loser. The refined momentum strategy goes loser minus winner in months of high volatility and in months of low volatility, the refined momentum strategy is winner minus loser.

Volatility in the regressions was not statistically significant for the 6-month value weighted strategy. Despite this, it is the only portfolio where refined momentum outperforms the standard momentum strategy. Interestingly, the drawdowns to refined momentum, on this strategy, are better than the standard momentum strategy during the financial crisis. However, the return difference is marginal at 0.23%, which is not statistically significant. Therefore, the refined momentum strategy does not statistically or economically outperform the standard momentum portfolio.

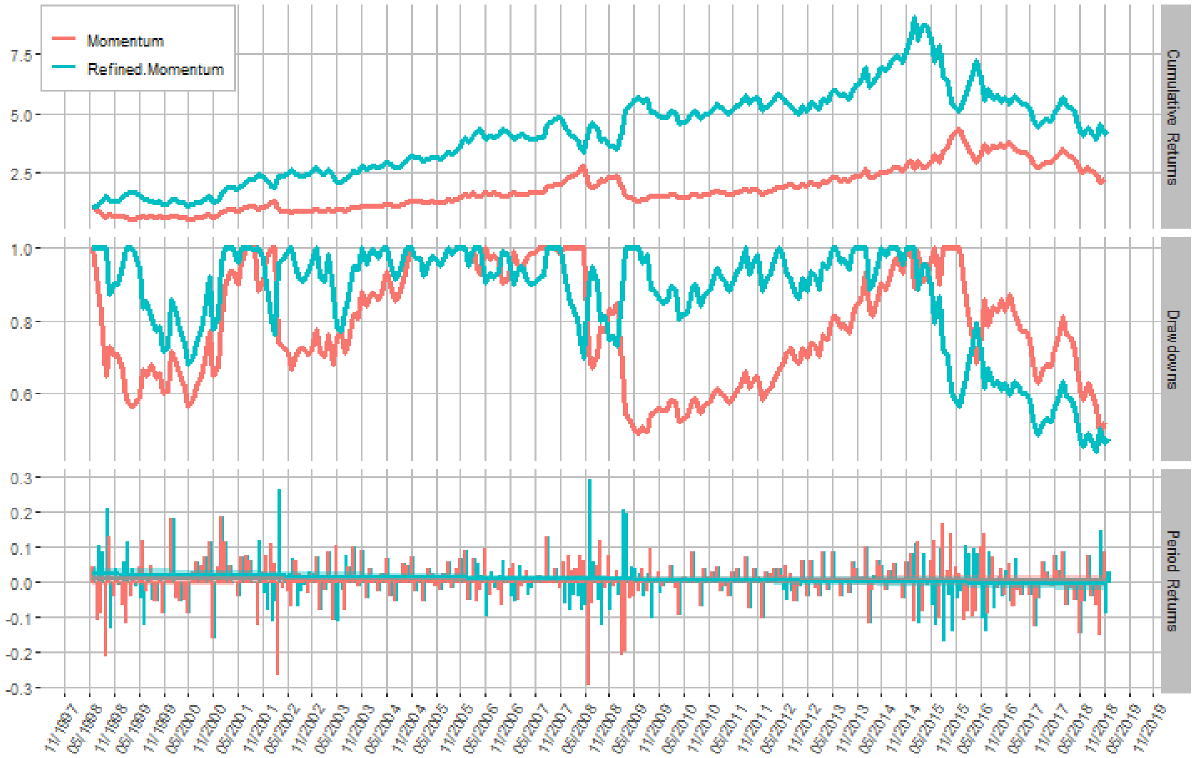

Figure 7 Momentum and Refined Momentum - 6-month value weighted strategy

Since volatility was statistically significant on the 6-month value weighted portfolio, the results on this strategy are of interest. If volatility cannot be utilised to enhance the performance of the one portfolio where volatility was significant, then volatility does not explain time variation in momentum payoff. This shows that the association between momentum payoff and volatility on this strategy is very weak.

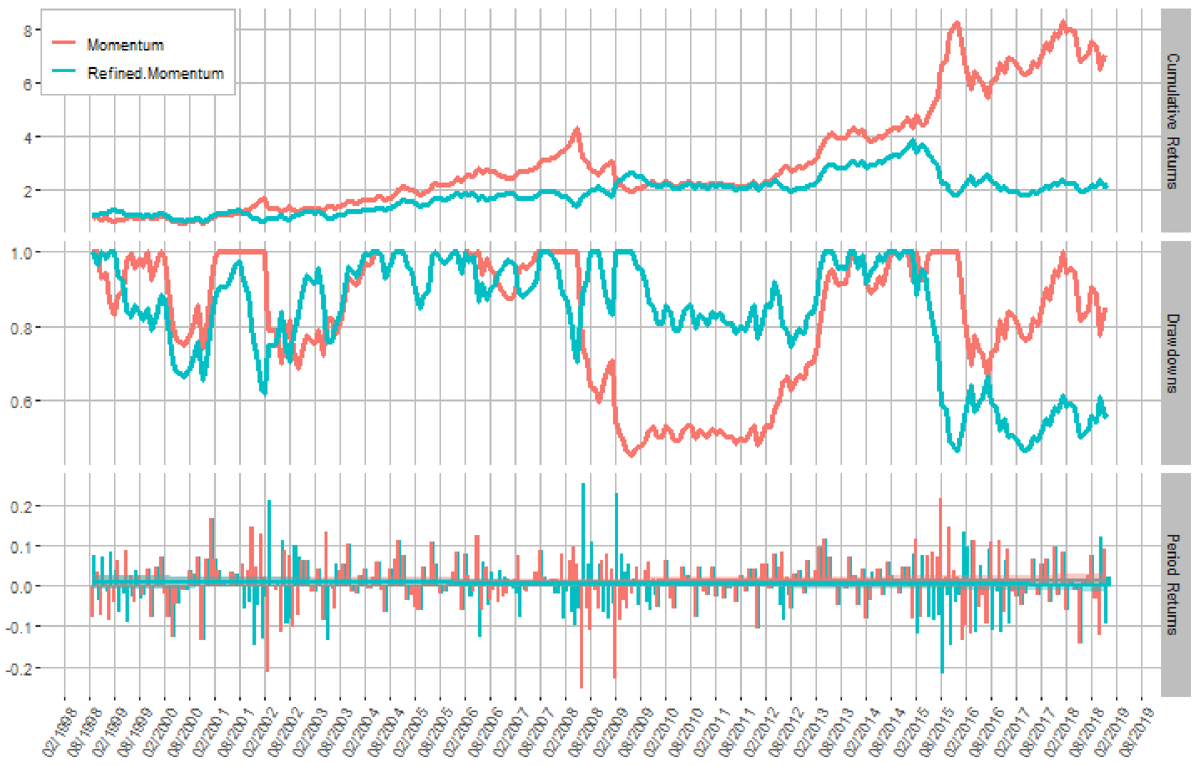

Figure 8 Momentum and Refined Momentum - 9-month value weighted strategy

The difference in means between the refined momentum strategy and standard momentum is not statistically different from zero for the rest of the strategies. Once again, the drawdowns of refined momentum in the financial crisis fair massively better over the drawdowns of the standard momentum portfolio.

It appears that the refined momentum strategy completely fails due to the 2016 momentum crash on the JSE, which does not coincide with lagged volatility. As a result, the refined strategy fails to switch to a loser minus winner strategy during the time when losers experienced extreme reversals.

The concept behind Wang and Xu (2015) refined momentum is that volatility is used to predict when losers will reverse. This fails to occur with momentum on the JSE. Therefore, the conclusion is that volatility does not enhance the performance of momentum in a predictable manner. This result is in direct contradiction to the findings of Wang and Xu (2015) who show that volatility can be used to increase the return to a momentum strategy.

The results show that although momentum is a global phenomenon, momentum is still country specific, with different factors affecting momentum in different countries. For instance, according to the US literature, volatility has a severe effect on momentum. In South Africa, no such effect is observed. Another counter example to the US literature is the Lin, Ko, Feng and Yang (2016) study, which replicates the Wang and Xu (2015) method for the Taiwan market finding that volatility has no explanatory power for time variation in momentum profits on the Taiwan market.

The results of all the momentum portfolios show that volatility has almost no effect on most momentum strategies. The 6-month strategies are clearly vulnerable to volatility, largely due to small stocks. Why this only affects the 6-month strategies is not certain. The repercussions of this is that momentum is robust to market conditions, macroeconomic factors and volatility swings. This makes momentum more of a puzzle than originally thought. Default risk makes a predictable dent on some momentum portfolios, but most are robust to this. Recall that the aim of this study is to determine if time variation in momentum profits can be explained by volatility or market state, such that momentum strategies can be enhanced by volatility or market state. This does not appear to be the case, despite all momentum strategies having a distinct decline in profitability in through time. This time variation in momentum remains unexplained by the results, and it remains to be seen if anything else can explain momentum.

4.9 DISCUSSION AND INFERENCE

Following the description of the results earlier, this chapter of Chapter 4 provides in depth analysis and discussion of the findings. The aim of this chapter is to attempt to provide a theoretical explanation of the results reported in Chapter 4. The relationship between momentum and each of the main variables of interest are discussed in different subchapters. Moreover, each subchapter provides insight into the relationships between momentum and the variables.

The tests show that for the most part, volatility is does not have a significant relationship with momentum regardless of portfolio construction methodology. The same is true for market state and when volatility is paired with market state. The main aim of the research is to test if a change in momentum payoff can be explained by a change in volatility. Of course, during the financial period, momentum strategies performed poorly. But the key here is a predictable drop in momentum when volatility increases throughout the sample, not just in a sub period. For example, in 2015 and early 2016, the winner minus loser differential was negative as losers reverse hard. However, this does not coincide with a substantial increase in volatility.

4.9.1 Momentum and Volatility

With the exception of the 6-month value weighted portfolio, among all lookback periods and using both equally weighted and value weight portfolios, volatility is not statistically significant in tests for explanatory power of time varying momentum. Table 35 summarises the results from univariate volatility regressions. The first two columns report whether the coefficient was statistically significant or not. The latter two columns report the sign on the coefficient. Even though one cannot regret the null hypothesis that the coefficients are not statistically different from zero, the signs of the coefficients are of interest as they show the relationship between momentum and volatility through time. The hypothesised relationship between momentum and volatility is negative. However, from the results in Table 35 below, the 3-month momentum strategy on value weighting has positive relationship with volatility. With that being said, since only one of the coefficients are statistically significant, the relationship may as well be non-existent, regardless of the sign on the coefficients.

Table 35 Volatility regression results summary – 12-month market volatility

	Equally Weighted	Value Weighted	Equally Weighted	Value Weighted
3	Insignificant	Insignificant	Negative	Positive
6	Insignificant	Significant	Negative	Negative
9	Insignificant	Insignificant	Negative	Negative
12	Insignificant	Insignificant	Negative	Negative

The question is why is volatility not significant in explaining time varying momentum payoffs? This is not an easy question to answer. The first thing to consider here is why volatility significant in the study by Wang and Xu (2015) for the US. As mentioned earlier, the financial crisis of 2009 was a key reason for this. In particular, the phenomenon of losers reversing harder than winners in 2009, leading to the extreme negative payoffs of momentum. More importantly, the timing of the volatility and momentum losses is what causes the explanatory power of volatility for momentum payoff in the US. In the US, extreme volatility lags the losses to momentum. As was shown in Figure 3, this does not appear to be the case for South Africa. The most volatile months did not precede the worst months for momentum. As can be seen from Figure 3, the market volatility increases from mid-2008 to late-2008, after which it begins to reduce. If lagged values of volatility can explain changes in the payoff to momentum in time, it is precisely after this period when one should observe a distinct pattern in the change to momentum payoff. From Figure 3, the changes appear to be random with no clear observed pattern or relation to changes in volatility.

An anomaly with the staying power of momentum would imply that there is a behavioural effect causing it otherwise it would have been arbitraged away. However, even though momentum exists on the JSE like it does in the US, it seems that what drives momentum on the JSE is different to what drives momentum in the US. This is evident from the lack of a statistically significant relationship between momentum and volatility on the JSE. Prolonged market volatility seems to have a profound effect on the behavioural patterns that cause momentum in the US but the same cannot be inferred for momentum on the JSE.

It is possible that the behavioural forces for momentum on the JSE may be stronger than the behavioural forces for momentum in the US. Additionally, this offers stronger evidence for momentum being a behavioural effect, since time varying momentum cannot be explained by volatility in South Africa, despite it being able to do so in the US. Alternatively, it could be that prolonged market volatility causes US market participants to change their behaviour in a manner that leads to momentum losing profitability. In this sense then the losses to momentum may just be coincidental due to market volatility causing widespread panic. However, this seems unlikely considering that the losses to momentum appear to be systematic following prolonged high market volatility.

On the other hand, volatility was statistically significant for the 6-month value weighted strategy. It is possible that a look back period of 3-months is too short and 12-months too long to capture the effect of a 12-month period of volatility. Therefore, it is tempting to conclude that using a period of 12-months for volatility, then volatility only seems to affect momentum when it is constructed with 6-months prior return. It begs the question then, why doesn’t the equally weighted portfolio achieve the same results? One suspicion might be that since value weighting causes some stocks in the portfolio to end up with larger weights, if volatility affects the return to a few of the stocks in the portfolio with large weights, this affects the entire portfolio negatively. It can then be concluded that the combination of a 6-month lookback period and value weighting leads to a momentum portfolio that has its return affected by volatility.

Overall, with only one portfolio out of eight having a statistically significant coefficient on volatility, it can be concluded that volatility does not have explanatory power for momentum payoff through time on the JSE. At least this is certainly the case when market volatility is defined using the lagged 12-month standard deviation of market returns.

When market volatility is defined as the lagged 6-month daily standard deviation of market returns, the results are slightly different. With this definition of market volatility, only one out of the eight strategies have a statistically significant coefficient on volatility. The 6-month value weighted strategy still has a statistically significant coefficient on volatility, this time at significant at the 1% level. This was the same strategy that had a statistically significant coefficient in the regressions with 12-month market volatility. The results are summarised in the table below.

Table 36 Volatility regression results summary – 6-month market volatility

	Equally Weighted	Value Weighted	Equally Weighted	Value Weighted
3	Insignificant	Insignificant	Positive	Positive
6	Insignificant	Significant	Negative	Negative
9	Insignificant	Insignificant	Negative	Negative
12	Insignificant	Insignificant	Negative	Negative

These results add some credence to the earlier intuition that a 12-month period on volatility may be too long to see an effect on the shorter strategies. The 6-month volatility being significant on the 9-month equally weighted strategy in this case shows that indeed 12-month volatility period may be too long. Volatility in this case also has explanatory power for the 6-month value weighted momentum portfolio. As was the case with the 9-month lookback period and 12-month volatility, the 6-month equally weighted portfolio regression does not produce a statistically significant coefficient on volatility. It could be the same effect occurring here, that value weighting up weights stocks that get affected by volatility more, which affects the entire portfolio.

It appears then that looking back 12-months on returns provides a long enough window to circumvent the effects of volatility on the payoff to momentum. Specifically, both the 6-month and the 12-month lagged volatility do not seem to interfere with the 12-month momentum construction in a significant manner. In the same vein, the 3-month lookback period appears to be much too short for lagged market volatility to have an effect on this kind of portfolio construction. The intersection of a lookback period of 6-months and a lagged 6-month volatility only seems to have an effect if the portfolio is constructed on a value weighted basis. The conclusion from this therefore, is that investors constructing momentum on a 6-month basis need to be weary of the lagged 6-month market volatility. It is interesting that both the lagged 6-month and lagged 12-month market volatility were significant on the 12-month momentum portfolio used by Wang and Xu (2015). This may be a hint that the momentum anomaly exists on the JSE due to factors that are different to the ones that cause momentum in the US. It is also quite possible that these factors are stronger on the JSE than they are in the US.

Another potential explanation for the difference in results, is that the JSE is structurally a different market to the NYSE. As Van Rensburg (2002) explains, the JSE has historically been a resource dominated market. As Van Rensburg (2002) states, the return generating process of the JSE is driven by a two-market segmentation. To be precise, the JSE returns are driven mainly by resource shares and industrial shares. There is also a large dominance of financial shares on the JSE. These are some of the factors that could contribute to volatility not having a significant effect on the payoff to momentum. In addition, South Africa differs culturally to the United States, which could mean that investors behave slightly differently on the JSE to investors in the US. This means that the momentum anomaly manifests itself for potentially different reasons on the JSE than in the US. For this reason, it is difficult to identify exactly why volatility does not have a significant effect on momentum on the JSE.

Lastly, the payoff to momentum experiences a monotonic reduction through time. Therefore, the overall trend in the data is a steady decrease in momentum payoff. This means that unless volatility also decreases steadily in time, momentum and volatility are unlikely to have a significant relationship through time. In order for something to sufficiently explain time varying momentum payoff, it would also need to have a steady trend through time, either decreasing or increasing. If it increases through time, it would have a negative association with momentum payoff through time, whereas if it decreases through time, it would have a positive association with momentum payoff through time. A potentially good candidate for this is liquidity, which has been shown to increase on the JSE over time (Young & Auret, 2018).

However, research of such nature must proceed with caution. The relationship between volatility and liquidity must not just be by chance. There needs to be a theoretical reason why increased liquidity should reduce momentum payoff. Young and Auret (2018) show that the JSE experienced two structural breaks that increased liquidity on the JSE. One was the move to a completely electronic system and the other was the introduction of colocation, which allows clients to place computers closer to the exchange to reduce execution times. This facilitated high frequency trading, which reduced the arbitrage opportunities on the JSE. Young and Auret (2018) further show that return predictability has reduced substantially on the JSE. This is evidence that arbitrage opportunities have been diminished on the JSE. Therefore, future research can test if the removal of some of the limits to arbitrage has contributed to momentum decreasing through time.

4.9.2 Momentum and Market State

According to Cooper *et al*. (2004), the profitability of a momentum strategy depends on the state of the market. Specifically, the paper shows that momentum performs better when the 36-month market return has been positive than when the 36-month market return has been negative. Conversely, Wang and Xu (2015) do not find that market state has explanatory power for momentum payoff using both a 36-month market state and a 6-month market state. The results from Chapter 4.2 are more in line with the findings of Wang and Xu (2015). When market state is defined as the lagged 6-month market state, the results from Chapter 4.4.1 show that market state by itself is not statistically significant in tests for explanatory power of momentum payoff. The results are true across all eight strategies. The results are summarised in the Table 37.

Although one would expect that a positive market state should lead to significantly more positive returns on momentum portfolios, this is not the case. The reason to this may be that the momentum anomaly quite simply exists regardless of the state of the market. Recall that momentum is about return continuation, winners keep winning and losers keep losing. If the lagged 6-month return has been negative, there will still be some stocks that had positive returns in this period. These stocks get bought by investors thinking that the stocks will continue to do well. Stocks that do poorly are sold by investors thinking that the stocks will continue to do poorly. Therefore, winners get bid up, which increases their short-term return and losers get oversold, which decreases their short-term return.

Table 37 Market state regression results summary – 6-month market state

	Equally Weighted	Value Weighted	Equally Weighted	Value Weighted
3	Insignificant	Insignificant	Positive	Positive
6	Insignificant	Insignificant	Positive	Positive
9	Insignificant	Insignificant	Positive	Positive
12	Insignificant	Insignificant	Positive	Positive

The question has always been why does this happen and why don’t rational investors notice this pattern and arbitrage it away? Something of this nature tends to be caused by behavioural effects and a number have been proposed to explain momentum. That is not the point of this discussion here, the point is that regardless of what causes momentum, it does not seem to be affected by the state of the market. Investors buy winners and sell losers in positive and negative markets. If anything, one should actually expect a negative market state to cause investors to bid up winner stocks even more. As investors seek positive returns in a down market, they bid up stocks that have done well in the down market and oversell stocks that have done poorly in the down market, more so than they would in an up market. Therefore, market state not been statistically significant across the board is not surprising.

Before a conclusion can be made, the original 36-month market state definition by Cooper *et al*. (2004) must also be addressed. The results of regressions using this version of market state are reported in Chapter 4.8.2 and a summary of the results is given in Table 38 below. Market state is not significant in any of the eight strategies. Therefore, the conclusion is that market state is not statistically significant in tests for explanatory power of momentum payoff.

Table 38 Market State Regression Results Summary – 36-month market state

	Equally Weighted	Value Weighted	Equally Weighted	Value Weighted
3	Insignificant	Insignificant	Positive	Positive
6	Insignificant	Insignificant	Positive	Positive
9	Insignificant	Insignificant	Positive	Positive
12	Insignificant	Insignificant	Positive	Positive

4.9.3 Momentum, Market State and Volatility

Wang and Xu (2015) find that market state and volatility work well together in explaining the payoff to momentum through time. To be precise, volatility in the down state works extraordinarily well with market state in tests for explanatory power of the payoff to momentum through time. This result is not matched by this study as volatility in the down state is only statistically significant on one strategy. This strategy was the 6-month value weighted strategy, which is the same strategy that had volatility as statistically significant. Volatility in the down state is significant in the regression results of one strategy. The results of these regressions are summarised in Table 39. Note that Table 39 is only for coefficients of volatility in the down state as volatility in the up state is not statistically significant in any of the regressions.

Table 39 Volatility regression results summary – Volatility in the down state

	Equally Weighted	Value Weighted	Equally Weighted	Value Weighted
3	Insignificant	Insignificant	Negative	Positive
6	Insignificant	Significant	Negative	Negative
9	Insignificant	Insignificant	Negative	Negative
12	Insignificant	Insignificant	Negative	Negative

The results show that the combination of prolonged negative market returns and an increase in market volatility does not influence seven out of eight momentum constructions. The reason why this is the case is not immediately obvious. It appears that the combination of an increase in volatility when the market return has been negative, does not seem to lead investors to abandon whatever behavioural biases that cause the momentum effect. This means that the behavioural biases that cause momentum on the JSE are robust to extraneous sources. On the other hand, the continuous drop in momentum payoff through time suggests that something is affecting momentum. Lo (2004) states that the profitability of any strategy should reduce over time as the strategy gets overcrowded.

An important avenue to discuss are the results of regressions with market state and volatility included together. Neither market state nor market volatility are statistically significant in any of the multivariate regressions on the eight strategies. Initially, only the 6-month value weighted strategy had volatility and volatility in the down state as statistically significant. This result remains robust with market state and volatility included together. For the rest of the strategies however, volatility and market state are not statistically significant together.

The non-significance of market state and volatility may be due to multicollinearity. However, the correlation between the two variables is -0.24 and the R-squared of the model is low. Additionally, the variance inflation factors are only marginally above one, which shows that the multicollinearity is not severe. Therefore, on the 9-month value weighted strategy, market volatility does not uniquely explain the variation in the payoff to momentum through time.

This result is not surprising given the low R-squared of the model when volatility is used by itself. This shows that despite the significant coefficient on volatility, the volatility data does not fit the overall trend in momentum payoff very well. This is demonstrated in Figure 5, which provides a visualisation of the overall trend in the data. The overall trend is negative, which shows that as market volatility increases, the payoff to momentum of the 9-month value weighted portfolio decreases. However, the variability of the data around the regression line is large. This means that the relationship is weak and when another variable is included, the relationship is hard to detect. If anything, the relationship is too weak to detect by itself.

Volatility in the down state and volatility in the up state are not statistically significant on any of the strategies when market state is included with them in the regressions. An important point to make here is that volatility in the down state is defined using market state. This means that volatility in the down state is negatively correlated to market state. This is because where market state has a 1, volatility in the down state has a 0 and where market state has a 0, volatility in the down state has market volatility. Indeed, the correlation between these two is -0.94, which is very close to being perfectly negatively correlated. The variance inflation factor between the two is 8.2584, which is above the general accepted level of 5. The tolerance is 0.1211, which is below the accepted level of 0.2. Therefore, it is likely that the insignificance of volatility in the down state is due to multicollinearity with market state. However, volatility in the down state is not statistically significant by itself in 7 out of 8 strategies. Therefore, the results may be valid. All in all, the results of volatility in market states and market state are difficult to interpret.

There is a possibility that the measures used for market state and volatility are misspecified and that the findings may be due to the limited investable universe available to investors on the JSE.

4.9.4 Volatility and Default Risk

An unexpected result of the study is the performance of default risk in the regressions. Although default risk is insignificant on 5 out of the 8 strategies, as seen in Table 40 below, default risk performs better than volatility. In addition, default risk on the same three strategies is still statistically significant when included with volatility and market state. Furthermore, default risk is significant in multivariate regressions of the 6-month value weighted strategy, while volatility and volatility in the down state are not. Recall that volatility and volatility in the down state were statistically significant in univariate regressions.

Table 40 Default risk regression results summary

	Equally Weighted	Value Weighted	Equally Weighted	Value Weighted
3	Insignificant	Insignificant	Negative	Positive
6	Significant	Significant	Negative	Negative
9	Significant	Insignificant	Negative	Negative

12	Insignificant	Insignificant	Negative	Negative

The relationship between default risk and the 9-month equally weighted momentum portfolio is clear to see from Figure 6 in Chapter 4.5. As soon as the probability of default shoots up around March 2008, both winner and loser portfolios experience massive drawdowns. Once probability of default tappers off and slightly decreases, both portfolios begin to recover. However, the loser portfolio recovers sooner than the winner's portfolio. This experience matches both Wang and Xu (2015) and Daniel and Moskowitz (2016) explanation that in market down turns, buying loser stocks is like buying options due to the asymmetric payoff. The initial increase in default risk causes investors to panic and sell everything. As investors begin to realise that the default risk priced in hasn't materialised, investors turn their attention to loser stocks looking for high returns. Therefore, default risk has a strong effect on the behaviour of investors, which ultimately affects the payoff to momentum.

Interestingly, default risk is not statistically significant for the 12-month strategies, the 3-month strategies and the 9-month value weighted strategy. Why this is the case is unclear. Perhaps the if a stock has been a loser over the prior 12 months, investors become convinced that its fate is sealed and hence buying this stock is unlikely to return a premium for them. However, if a stock has been a loser over 6 months in a distress period, investors might feel that the stocks have been affected by overall market conditions, such that loser stocks in the last 6 months are bought up in periods of high default risk.

Conversely, default risk is not significant for 3-month momentum, so the conjecture given above is contradicted by the results of the 3-month strategies. Perhaps 3-months is too short a horizon for investors to build confidence in whether default risk has been overpriced in a stock. Momentum constructed with a 3-month lookback period averages the lowest return of all the strategies.

The lack of a universal momentum strategy makes it difficult to draw conclusions about overall momentum. On one hand, significance on 3 strategies makes it unlikely to be random, so default risk does influence some of the strategies. However, since default risk is not significant for 5 out of 8 strategies, the conclusion is that, in general, momentum is not affected by default risk.

Notwithstanding that default risk is only significant on three portfolios, the results of default risk may still be an interesting avenue for research as a standalone factor on the JSE, especially considering the impact that ratings may have in South Africa. Given the link to status, and the link from that to many other capital elements such as FDI and international bond index holdings, perhaps this could indicate a factor which needs further exploration. For instance, one could investigate if it is important for the JSE that South Africa is seen as safe to invest in, given that the JSE is in many ways seen as an international indicator.

4.9.5 Size Balanced Momentum

Momentum is also constructed on size portfolios. The large capitalisation stocks are stocks that are in the top 50 in market capitalisation. The rest of the stocks in the bottom 50 are classified as small capitalisation stocks. Volatility and market state are not statistically significant on any of the large stock momentum portfolios, not even the 6-month value weighted portfolio, which previously had volatility and volatility in the down state as statistically significant.

When momentum is formed on small stocks, the results are slightly different. These results are summarised in Table 41 below. Volatility is statistically significant on two out of eight strategies, both being the 6-month strategies. The results show that any explanatory power that volatility has is centred on small stocks. The lack of significance of the overall 6-month value weighted strategy seems to suggest that small stocks are a strong driver of returns to the overall 6-month value weighted strategy. One should be careful not to interpret this as a momentum and size interaction considering that this is only one strategy. Also, Page *et al*., (2016) find that the size effect on the JSE has largely disappeared.

Table 41 Volatility regression of momentum on small stocks results

	Equally Weighted	Value Weighted	Equally Weighted	Value Weighted
3	Insignificant	Insignificant	Negative	Negative
6	Significant	Significant	Negative	Negative
9	Insignificant	Insignificant	Negative	Negative
12	Insignificant	Insignificant	Negative	Negative

However, volatility does not remain statistically significant when included with market state. This shows that the results of volatility are not robust. The relationship between volatility and momentum on the 6-month portfolio is weak. These results point to the strength of the momentum anomaly on the JSE, which partially explains the strong persistence of profitability of the strategies. If momentum is robust to volatility, economic and stock market conditions, virtually the only forces standing in the way of momentum are behavioural and structural.

Structural being elements like liquidity, although a full study on momentum and liquidity is required to determine this.

5 CONCLUSION

This chapter concludes the study by summarising the main findings and providing recommendations for future research.

The objective of this study was to determine if volatility has explanatory power for time varying momentum payoff. This follows the results of Wang and Xu (2015), who find that volatility is significant in tests for explanatory power of time varying momentum payoff on the US market. The implication of which is that when market volatility increases, the payoff to momentum decreases, signifying a negative association between volatility and momentum. In addition, the study aimed to test if market state has explanatory power for momentum payoff. This follows the results of Cooper *et al*., (2004) who find that momentum profits are positive following a positive market state and momentum profits are negative following a negative market state.

Chapter 4.2 reported results of univariate and multivariate regressions of momentum payoff on volatility and momentum. Momentum portfolios are constructed using lookback periods of 3, 6, 9, and 12-months. Both value weighted and equal weighted portfolios are considered. Market volatility is the lagged 12-month daily standard deviation of market returns. Market state is the based on the lagged 6-month market return. A month is in a positive market state if the lagged 6-month return is non-negative, otherwise the month is in a negative market state.

In univariate regressions market volatility is not statistically significant at the 5% level on 7 of the 8 portfolios. The only portfolio with a statistically significant coefficient on volatility is the 6-month value weighted portfolio. When volatility is included with market state, all but one of the portfolios do not have a statistically significant coefficient on volatility. The one exception being the same 6-month value weighted portfolio. Therefore, volatility does not have explanatory power for momentum payoff on the JSE. This means volatility has no effect on momentum payoff in South Africa.

The results for volatility in the down state are the same as volatility, with only the 6-month value weighted portfolio returning a statistically significant coefficient on volatility in the down state. Volatility in the down state remains statistically significant in the presence of market state. Volatility in the up state is not statistically significant in any of the regressions. It is important to note including volatility in up and down states is problematic as it is difficult to interpret this result given that market state is used to define volatility in the down state. As a result, the two variables are highly correlated. Therefore, it is possible that when market state is included with volatility in the down state and volatility in the up state, either one is not statistically significant due to multicollinearity.

Market state is not statistically significant across all portfolios in both univariate and multivariate regressions. Table 2 shows that the payoff to momentum is positive following both positive and negative market states for all portfolios except for the 3-month value weighted portfolio. Actually, some momentum strategies actually average a higher payoff in down market states. The 3-month portfolio has a negative payoff in down market states, the only portfolio with a negative payoff in negative market states.

Chapter 4.6 presents results of regressions when size is considered with momentum. Large capitalisation firms are classified companies whose shares occupy the top 50 shares when ranked by market capitalisation. Shares that fall outside of this threshold are small cap shares. When momentum is constructed on large stocks, none of the portfolios have a statistically significant coefficient on volatility or market state.

When momentum is constructed on small stocks, volatility is statistically significant on 2 of the 8 small stock momentum portfolios. However, neither of the two portfolios retain a statistically significant coefficient on volatility. This shows that the results of volatility are not robust on the 6-month small stock strategies.

Defining volatility with a window of 6 months does not change the results at all. The 6-month value weighted portfolio is still the only portfolio with a significant coefficient on volatility. Also, using Cooper *et al*., (2004) 36-month window for defining market state does not change the results of market state. This is not surprising considering that market state was not significant with a shorter window. In addition, only 1% of the months are in down market states with this definition, which significantly reduces the power of the tests.

An unexpected result of the study is the performance of default risk, which is found to have explanatory power for 3 out of 8 momentum strategies. This can be attributed to the asymmetric payoff of loser stocks in periods of high probability of default. If the default does not materialise then investors receive a huge premium, hence loser stocks become attractive when probability of default is high. However, the 12-month and 3-month strategies as well as the 9-

month value weighted strategy do not have a statistically significant coefficient on default risk. Therefore, the conclusion is that, with the exception of a 6-month lookback period, default risk has no effect on momentum.

For the most part, the results of this study differ from the results of Wang and Xu (2015). The result that volatility has no explanatory power for momentum is robust. A reason for this might be the two-market segmentation of the JSE documented by Van Rensburg (2002). Another reason might be that although momentum exists in the US as well as on the JSE, both are driven by different factors. Many of the proposed explanations of momentum are behavioural, so it is possible that the behavioural biases of investors on the JSE that create momentum are either stronger or different to the behavioural biases of investors in the US that causes momentum. It is possible that outside of specific momentum portfolios, investors in the US are not affected by volatility enough for them to abandon the behavioural biases that cause momentum.

This study also serves as an out of sample test for the refined momentum strategy proposed by Wang and Xu (2015). The refined strategy reverses the winner minus loser momentum strategy in months of high volatility so that the portfolio is now loser minus winner. A month is of high volatility if the lagged 12-month daily standard deviation of market returns is higher than the 36-month daily stand deviation of market returns. Wang and Xu (2015) find that the refined strategy dramatically outperforms the standard momentum strategy. The results of this study show that this is not the case for any portfolio, even the ones that had volatility as statistically significant in regressions. This shows that overall volatility does not have significant explanatory power for momentum on the JSE.

Future research can consider other time series tests of explanatory power for momentum on the JSE. This study, as well as Page *et al.* (2013), find that momentum experiences a monotonic decrease in the momentum payoff through time. The lack of statistical significance for volatility and market state for momentum through time calls for more time series tests of momentum. A potential avenue to pursue is the relationship between liquidity and momentum through time.

In addition, further research into more sophisticated definitions of market state and market volatility might aid to better identify the effect that market cycles have on momentum profits. A prospective angle might be to use non-linear modelling to classify market states.

Lastly, the unexpected outperformance of default risk over volatility suggests that default risk has been neglected as a factor on the JSE in the literature. Further research can be undertaken to investigate the impact that default risk may potentially have for returns on the JSE.

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7 APPENDIX

Table 42 Granger causality tests - MOM, DIV, TERM

Lag	MOM to DIV	DIV to MOM	MOM to TERM	TERM to MOM
1	0.324993	0.610742	0.456277	0.370632
2	0.714519	0.63852	0.764516	0.40173
3	0.530322	0.734022	0.121571	0.193414
4	0.414329	099653	0.783884	0.049155
5	0.936182	0.999503	0.585787	0.420691
6	0.425492	0.816802	0.839378	0.738096
7	0.280914	0.7749	0.707535	0.899534

Table 43 Granger causality tests - MOM, DEF, FEARS

Lag	MOM to DIV	DIV to MOM	MOM to TERM	TERM to MOM
1	0.828204	0.440982	0.669317	0.517609
2	0.889395	0.534011	0.906525	0.952376
3	0.610222	0.513128	0.499324	0.746231
4	0.539596	0.947819	0.652805	0.904317
5	0.537928	0.754931	0.694635	0.331248
6	0.262559	0.940718	0.502284	0.770365
7	0.223047	0.735008	0.987216	0.756732

Table 44 Granger causality tests - MOM, FEARS, SAVI, SEMI, RD

Lag	MOM to FEARS	FEARS to MOM	MOM to SEMI	SEMI to MOM	MOM to SAVI	SAVI to MOM	MOM to RD	RD to MOM
1	0.4566	0.7694	0.512	0.343	0.4359	0.1742	0.8355	0.7844
2	0.1226	0.4331	0.6368	0.4337	0.6736	0.3779	0.9053	0.3869
3	0.6535	0.2869	0.4292	0.2854	0.7813	0.3047	0.5298	0.302
4	0.1384	0.9579	0.7721	0.5652	0.531	0.6092	0.7022	0.8041
5	0.2329	0.4415	0.9714	0.1251	0.6156	0.8921	0.2095	0.454
6	0.9886	0.142	0.5171	0.3138	0.7574	0.9029	0.4941	0.9142
7	0.7669	0.1165	0.516	0.7364	0.8799	0.6641	0.5552	0.9829