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Residual momentum and investor sentiment on the Johannesburg Stock Exchange (JSE)

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Abstract

Momentum has been described as the premier financial market anomaly (Fama & French, 2008), but styles based on this phenomenon tend to suffer intermittent crashes (Barroso & Santa-Clara, 2015). The study investigated a variation on momentum that considers only firm-specific returns, determined from the residual remaining after deducting returns attributable to common risk factors, when selecting portfolio constituents. This prevents concentrated exposure to common risk factors in any one portfolio. The method is known as residual momentum and has shown great promise to improve risk-related returns.

Investor sentiment is another financial market phenomenon and is often explained by means of the same behavioural factors as momentum. The study also considered the effect of investor sentiment on momentum in order to document the effect on the JSE, to shed further light on the driving factors behind the phenomena, and to explore practical investment opportunities.

Equally weighted conventional momentum and residual momentum portfolios were constructed from the largest 160 stocks on the JSE on a quarterly basis over the last 27 years in order to compare the styles' performances. In addition, momentum returns were compared across different sentiment states, defined based on the level of investor sentiment as proxied by a consumer confidence index orthogonalised to various macroeconomic variables.

Residual momentum was found to provide better risk-adjusted returns than conventional momentum on the JSE. Investor sentiment showed an effect on momentum styles, with residual momentum most profitable following pessimistic formation periods and conventional momentum most profitable following non-pessimistic periods.

Keywords

Anomalies, momentum, residual momentum, investor sentiment

Declaration

I declare that this research project is my own work. It is submitted in partial fulfilment of the requirements for the degree of Master of Business Administration at the Gordon Institute of Business Science, University of Pretoria. It has not been submitted before for any degree or examination in any other University. I further declare that I have obtained the necessary authorisation and consent to carry out this research.

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1.1 Research Title

Residual momentum and investor sentiment on the Johannesburg Stock Exchange (JSE)

1.2 Research Problem

Momentum is an enduring market anomaly and, if used effectively, could potentially allow for excess profits to an active investor. However, it is susceptible to occasional substantial losses due to the way in which it is formulated. An alternative formulation strategy, called residual momentum, could reduce this risk, but has not been tested in the South African market. Residual momentum also allows for renewed examination of the drivers behind momentum through investigating the effect of investor sentiment on both residual and conventional momentum. Consideration of this effect could lead to enhanced practical trading strategies.

1.3 Background

Since the advent of financial markets, investors have always striven for methods to obtain superior returns. This has been found to be an exceedingly difficult task. The Efficient Market Hypothesis or EMH (Fama, 1970), a once dogmatic and still widely accepted market theory, precludes this absolutely in its strong form. Even the weak form of the theory states that all past public information of a stock has already been taken into account in its pricing. However, a number of anomalies (Banz, 1981; Basu, 1977; Jensen, 1978) have been empirically observed in the market, putting pressure on the ability of the EMH to accurately explain the behaviour of the market.

The recognised anomalies have been incorporated into a variety of investment strategies and styles, of which momentum investing has been one of the most enduring. This is based on the observed phenomenon of continuation of stock prices in the short term and reversal in the longer term. Fama and French (2008) referred to it as the "premier anomaly" (p. 1653). Muller and Ward (2013), in a study comparing a number of investment styles, found momentum to be the most profitable investment style on the JSE.

A significant problem with momentum as a strategy is that, despite its proven performance, it has a propensity for catastrophic crashes. The crash risk of momentum strategies were found to be due to a concentration of low and high beta stocks in winner and loser portfolios respectively during a market downturn. When the market suddenly recovers, the momentum strategy shows a significant loss (Barroso & Santa-Clara, 2015; Daniel & Moskowitz, 2013; Grundy & Martin, 2001). The above applies to any systematic risk factor and not only market risk. A method that utilised only the risk-adjusted residual returns to determine the winner and loser momentum stocks recently emerged as a way to reduce exposure to common risk factors (Blitz, Huij & Martens, 2011). In the United States (US) this method, known as 'residual momentum', has shown remarkable improvements in risk-adjusted returns over conventional momentum strategies, but is yet to be investigated in the South African market.

Furthermore, to effectively utilise momentum as a strategy, it is important to understand the drivers behind it. There exists a wealth of literature attempting to reconcile the anomalies, including the momentum effect, to the EMH through traditional or behavioural finance theories. While the literature is not unanimous, the overwhelming majority appear to subscribe to behavioural factors as explanations for these anomalies. Momentum has been described by means of investor biases such as conservatism and representativeness (Barberis, Shleifer & Vishny, 1998), self-attribution and overconfidence (Daniel, Hirshleifer & Subrahmanyam, 1998), positive feedback trading (De Long, Shleifer, Summers & Waldmann, 1990), bounded rationality and a slow rate of news diffusion across the market (Hong & Stein, 1999), herding (Bikhchandani, Hirshleifer & Welch, 1998) and the disposition to realise paper gains, but not paper losses (Barberis & Xiong, 2009; Shefrin & Statman, 1985).

The behavioural finance theories accept that investors do not always make decisions rationally or take all available information into account. Investor sentiment, as a concept, takes this one step further and considers how investors' biases and heuristics are affected by their emotions and prevailing sentiment. If there is an effect evident and if the behavioural explanations for momentum hold true, it stands to reason that investor sentiment could have an effect on momentum in the market.

The direct relationship between these two constructs only came to the fore in recent literature. Antoniou, Doukas and Subrahmanyam (2013) found investor sentiment to significantly affect momentum. Momentum only occurred during periods of positive investor sentiment and disappeared completely during periods of negative sentiment. They hypothesised that news that contradicts investors' prevailing sentiment causes cognitive dissonance in the minds of investors and slows the diffusion of news.

Further investigation into the relationship between momentum and sentiment sheds more light on the drivers behind these stock market phenomena, especially with regard to risk exposure. Studies on investor sentiment have found small, high growth stocks to be more sensitive to levels of investor sentiment (Baker & Wurgler, 2006; Mian & Sankaraguruswamy, 2012). Similar to the reason for momentum crashes described earlier where, for example, winner portfolios become loaded with high beta stocks during bull markets, winner portfolios could become loaded with sentiment-sensitive stocks during periods of optimism.

The use of residual momentum portfolios reduces the risk of overexposure to extreme size, value/growth or a specific industry's stocks in any one portfolio and could thereby make the strategy less dependent on investor sentiment. A comparison of the effect of investor sentiment on conventional and residual momentum strategies advances the literature on the understanding of both momentum and investor sentiment.

1.4 Research Motivation and Aim

The research consists of two major parts.

Part one considers the relative risk and profitability of a momentum strategy based on stocks' residual returns on the JSE and how this compares to conventional raw price momentum strategies. Conventional literature on momentum strategies employed the construction of portfolios based on stocks ranked according to absolute (or relative to a benchmark) price movements during the formation period. The study investigates the use of residual returns momentum to rank stocks to allow for the construction of winner and loser portfolios. Residual momentum utilises the residuals of stocks which refer to returns that cannot be attributed to common risk factors. This study accommodates size and value risk (Banz, 1981; Basu, 1977; Fama & French, 1992), as well as industry risk (Moskowitz & Grinblatt, 1999), in its computation of residual returns.

Part two investigates the effect of investor sentiment on momentum strategies on the JSE. The effect of investor sentiment on residual momentum, which have not been studied either locally or internationally, is primarily examined. Evidence from the literature predicted positive returns for a conventional momentum strategy only following periods with positive investor sentiment. The applicability of these findings in the South African market is determined.

1.4.1 Academic Rationale for the Research

The research is in essence a replication and combination of the work of Blitz et al. (2011) and Antoniou et al. (2013).

Replication is warranted due to the context of the JSE being significantly different from that of the US markets, particularly where momentum and investor sentiment are concerned. For example, factors such as size and value (Jegadeesh & Titman, 1993), industry factors (Moskowitz & Grinblatt, 1999) and liquidity (Page, Britten & Auret, 2013) have all been found to affect momentum. The JSE is only about one-twentieth the size of the New York Stock Exchange (NYSE) based on market capitalisation and number of firms listed, and it has a trade velocity only 30 percent that of the NYSE (World Federation of Exchanges, 2016). The dichotomous nature (Beelders, 2003; Muller & Ward, 2013) of the JSE, specifically differences between resource versus non-resource stocks (Barr, Kantor & Holdsworth, 2007), could also affect the response of the market to these phenomena.

Investor sentiment is ascribed to the irrationality of retail investors and limits to arbitrage (Baker & Wurgler, 2006). The JSE's lower liquidity and prohibition on naked short selling could increase the limits to arbitrage, resulting in greater sentiment effects than in other markets. Constraints imposed on institutional investors regarding short sales and specific firm exposure result in concentrated investing activities on the JSE and increased limits to arbitrage in this market (Raubenheimer, 2012).

While the existence of both momentum (Hoffman, 2012; Muller & Ward, 2013; Page et al., 2013) and investor sentiment (Dalika & Seetharam, 2015) have been confirmed on the JSE, neither residual momentum nor the direct relationship between sentiment and momentum of any type have been sufficiently investigated. The effect of investor sentiment on residual momentum is unstudied internationally.

International literature on residual momentum in general is also quite recent (Blitz et al., 2011; Gutierrez & Pirinsky, 2007) and thus relatively scarce. While many earlier studies on momentum did consider market risk factors, they usually tested for this only as a robustness check of their findings. Commonly, the risk exposure of conventionally constructed momentum portfolios (Antoniou et al., 2013; Cooper, Gutierrez & Hameed, 2004; Jegadeesh & Titman, 1993) were tested. Residual momentum's construction of portfolios using only idiosyncratic, risk-adjusted returns allows for more direct testing of the source of momentum profits. This research thus adds to the overall body of knowledge on momentum and residual momentum in particular.

Regarding the second part of the research, the effect of investor sentiment on momentum has also gained prominence in recent literature (Antoniou et al., 2013; Hühn & Scholz, 2016; Stambaugh, Yu & Yuan, 2012). Few studies have investigated the direct relationship between the two concepts, none of them on the JSE. With both constructs commonly explained along behavioural finance theories, the juncture of these concepts provides an opportunity for the testing of some of these behavioural theories.

In addition, residual momentum addresses over-exposure of momentum portfolios on firms with high loadings on size and value factors. These are two of the factors on which investor sentiment have been found to have the greatest cross-sectional influence (Baker & Wurgler, 2006). Comparing the returns of conventional and residual momentum strategies across different sentiment periods allows for greater understanding of the interaction between the constructs and the driving forces behind it.

1.4.2 Business Rationale for the Research

Internationally, residual momentum has been found to correlate closely to conventional momentum, but with much less volatility. It has also shown profits for longer, before reversion to the mean became evident (Blitz et al., 2011; Gutierrez & Pirinsky, 2007). Because residual momentum strategies attempt to disregard profits due to systematic size, value and industry risks, the winner and loser portfolios are less likely to become loaded with either high or low risk stocks. This results in these strategies being more resistant to large losses during sudden market turnarounds (Blitz et al., 2011).

Evidence of the performance of residual momentum in the South African market is provided. This holds implications for real-world traders regarding their application of momentum investing. Residual momentum offers a viable alternative to conventional momentum depending on the mandate, investment goals and risk appetite of the trader. This study also establishes the optimal formation and holding periods for a residual momentum strategy on the JSE.

On the relationship between sentiment and momentum, the results of Antoniou et al. (2013) hold far-reaching implications for investors in the US in that they should only utilise momentum based trading strategies during periods of optimism in the market. This study provides information which could be used by investors in the South African market to guide decision making on whether and when to consider sentiment in a momentum based investment strategy.

Ultimately traders' momentum strategies can be meaningfully improved through dutiful consideration of the use of residual momentum and the implications of investor sentiment on momentum strategies.

2 Literature Review

2.1 Introduction

A market is deemed to be efficient when share prices "at any time fully reflect on all available information" (Fama, 1970, p. 383) and "with respect to (a certain) information set … if it is impossible to make economic profits by trading on the basis of (the) information set" (Jensen, 1978, p. 97). The Efficient Market Hypothesis (EMH) was formally defined by Fama (1970), building on the then re-emergent random walk theory which stated that "the future path of the price level of a security is no more predictable than the path of a series of cumulated random numbers" (Fama, 1965, p. 34).

EMH quickly gained prominence to become the dominant market theory during the 1960s and 1970s and is still being applied today. However, over time, more and more evidence of so-called anomalies emerged (Banz, 1981; Basu, 1977; Jensen, 1978).

To understand what is meant with anomalies, one has to first consider EMH in more detail. It is normally defined in terms of three categories (Fama, 1970):

- Strong form market efficiency means that prices react efficiently when all information is considered, even those to which some person or group has a monopoly
- Semi-strong form market efficiency means that all publicly available information is accurately reflected in the stock price
- Weak form market efficiency means that all historical price information is considered and reflected in the stock price

Various anomalies have been observed in the market, indicating violations of the EMH to varying degrees. A word of caution with regard to anomalies in the market is the so-called joint hypothesis problem where efficiency can only be tested using a mathematical model of the market (Fama, 1991). Any evidence of anomalous behaviour could thus perhaps only mean that the market model is incomplete and not necessarily that the market behaves inefficiently. Sharpe (1964), Lintner (1965) and Mossin (1966) all contributed to the formulation of probably the most well-known market model, namely the Capital Asset Pricing Model (CAPM), which provided a rational model for the relationship between risk and expected returns of shares on the market. Using the CAPM as the market model, early anomalies found included increased future returns on stocks with low price-to-earnings ratios (Basu, 1977) and on stocks with small market capitalisations (Banz, 1981).

This highlighted the limitations of the CAPM and research started to focus on alternative, empirically-derived asset pricing models such as the Fama-French three factor model (Fama & French, 1992) or the more general arbitrage pricing theory (Roll & Ross, 1980).

A factor which has been described as the "premier anomaly" (Fama & French, 2008, p. 1653) in financial markets is that of momentum. Momentum is based on the empirical findings that stocks that performed well in the recent past tend to continue to perform well in the short-term with a reversal generally evident in the long run. It has been incorporated into updated asset pricing models (Carhart, 1997), but the drivers behind it, stock price under- and overreaction, has overwhelmingly been approached through a behavioural finance lens. It is also a very enduring anomaly as recent studies still found evidence of abnormal profits following a momentum trading strategy (Blitz et al., 2011; Hoffman, 2012; Muller & Ward, 2013).

Another important factor at play in financial markets that is in discordance with EMH is that of investor sentiment which also relates to behavioural finance. It assumes that investors do not behave rationally and that their decision making is influenced by their emotions (Baker & Wurgler, 2007). This possible influence on the behavioural factors underpinning other anomalies such as momentum means that investor sentiment should be considered in conjunction with these anomalies.

The existence of anomalies is ultimately important from a practical perspective as they provide windows of opportunity for active investors to obtain profits in excess of that of the market. The strong form of EMH means that no profits in excess of the market are possible through any means, including technical analysis. Even the semi-strong form only allows for profits if the trader is privy to impactful, non-public information. Understanding the anomalies is therefore imperative for any active investor.

2.2 Momentum

Momentum in financial markets relate to the phenomenon where a stock's past performance can predict subsequent performance. Stocks that performed well in the recent to medium term past continue to perform well in the short term (Chui, Titman & Wei, 2010; Daniel & Moskowitz, 2013; Jegadeesh & Titman, 1993). Mean reversion also tends to occur on these stocks in the longer term (Antoniou et al., 2013; Hong & Stein, 1999).

Momentum as a phenomenon in financial markets is widely acknowledged and has been extensively studied. Evidence of its existence has been found in equity markets across the world (Asness, 2011; Chui et al., 2010; Fama & French, 2012; Jegadeesh & Titman, 1993). It has also been documented across industries (Moskowitz & Grinblatt, 1999; Nijman, Swinkels & Verbeek, 2004; Su, 2011) and for other asset classes such as currencies (Menkhoff, Sarno, Schmeling & Schrimpf, 2012; Okunev & White, 2003), commodities (Miffre & Rallis, 2007; Novy-Marx, 2012; Shen, Szakmary & Sharma, 2007) and bond futures (Asness, Moskowitz & Pedersen, 2013).

Recent focus of the academic literature on momentum has been on reducing the crash risk associated with it. Barroso and Santa-Clara (2015) suggested scaling the exposure to the momentum strategy based on ex-ante forecasted volatility. Moskowitz, Ooi and Pedersen (2012) investigated what they called time-series momentum and found that a stock's own past returns could predict its future absolute returns. This was as opposed to conventional momentum studies that considered the cross-sectional performance of stocks in the market. They found that a diversified time-series momentum portfolio provided abnormal returns with low exposure to traditional risk factors. Blitz et al. (2011) followed an approach where risk factor exposure was eliminated as far as possible prior to portfolio construction, resulting in a strategy referred to as residual momentum.

2.2.1 Momentum on the JSE

Momentum studies on the JSE have in general found momentum to be a pervasive and persistent phenomenon (Muller & Ward, 2013; Page et al., 2013; Snyman, 2011). Muller and Ward (2013) found that an investment style based on momentum yielded profits superior to that of styles based on value or quality indicators. Their momentum portfolios were created by ranking shares based on their returns over the past 12 months and employing a holding period of three months. It must be noted that despite its success, momentum failed to provide profits in excess of the All Share Index (ALSI) during the last five years, 2007 to 2011, of the study.

Hoffman (2012) found persistent time-series correlation between recent historical portfolio returns and future returns even after adjustment for risk. This held true across different firm size categories.

Hsieh and Hodnett (2011) found evidence of mean reversion on the JSE. Mean reversion was asymmetrical between winner and loser portfolios, but the time to full reversion depended on the formation period studied. Winner and loser portfolios were also constructed from total returns.

Numerous other studies have investigated momentum on the JSE. It has been combined with momentum in firm fundamental indicators (Moodley, 2013), liquidity (Page et al., 2013), size and liquidity (Eltringham, 2013) and value (Fraser & Page, 2000). Momentum on the JSE was also studied in the recent period after the global financial crisis (Bolton & von Boetticher, 2015).

It must be noted that the above mentioned studies considered either total returns to compile momentum portfolios or applied a technical momentum indicator, such as a moving average or relative strength index, to a market index. The use of risk-adjusted or idiosyncratic returns to construct momentum portfolios do not appear to have been investigated on the JSE.

2.2.2 Residual Momentum and Conventional Momentum

Prominent earlier studies investigating momentum used cumulative raw or total returns in compiling winner and loser momentum portfolios (De Bondt & Thaler, 1985; Jegadeesh & Titman, 1993). Most subsequent academic studies, many of them mentioned earlier in this report, determined momentum in a similar fashion and thus the term 'momentum' in a financial context generally referred to this total returns momentum, henceforth conventional momentum.

Conventional momentum winner and loser portfolios considered total stock returns, thereby including market exposure and returns due to market related risk factors. These winner and loser portfolios could therefore become loaded with high and low beta stocks respectively if the market has been doing well. The reverse would be true if the market has had a poor run. A sudden market reversal from bullish to bearish would then leave the conventional momentum investor with a high beta winner portfolio that moves down pro-cyclically with the market while the low beta loser portfolio stays relatively stable, resulting in losses to the investor (Daniel & Moskowitz, 2013; Grundy & Martin, 2001).

The effect and potential losses could be even worse if the market showed a sudden recovery after a sustained run of poor results. The resultant high beta loser portfolio on which the investor had a short position would experience significant gains which would not be offset by gains in the winner portfolio as this would consist of low beta stocks. The net effect could be sizable losses for the conventional momentum investor (Barroso & Santa-Clara, 2015; Blitz et al., 2011; Daniel & Moskowitz, 2013).

The momentum studies mentioned earlier did not entirely ignore these risk factors, and usually checked the robustness of their findings against risk factors through models such as the CAPM and the Fama-French three factor model amongst others (Antoniou et al., 2013; Cooper et al., 2004). However, these tests were done after the fact on momentum returns and momentum portfolios as a whole. Alternatively, the effects of stocks' size and value, as captured by the Fama-French three factor model, on momentum were tested by first sorting stocks based on these factors and then determining momentum portfolios.

Residual momentum is an alternative momentum construct that considers only a stock's residual returns, as opposed to its total raw returns, to determine relative winners and losers when constructing momentum portfolios. This method limits the portfolios' exposure to market and other risk factors. Residual momentum portfolios are therefore less likely to become unduly loaded with stocks with similar risk exposure. An investment strategy based on residual momentum is consequently expected to have a lower crash risk than conventional momentum. This expectation has been found to hold true to varying degrees in American financial markets by a number of recent studies considering residual momentum or related strategies (Blitz et al., 2011; Cooper et al., 2004; Gutierrez & Pirinsky, 2007; Hühn & Scholz, 2016).

2.2.2.1 Determining Conventional Momentum and Residual Momentum

In their seminal work on momentum, Jegadeesh and Titman (1993) chose to "select stocks based on their return…" (p. 68). They went on to investigate the difference in average and total returns for their decile portfolios for firms of different sizes and different betas. A zero investment strategy was followed where the investor shorted the portfolio containing stocks that performed the worst and took a long position on the portfolio containing stocks that performed the best in the period preceding portfolio formation. Momentum portfolios were created based on stocks' relative total returns during the holding period. This methodology provided the blueprint for most subsequent studies on momentum.

De Bondt and Thaler (1985) asserted that they used residual returns in their work on market overreaction. They defined the residual as:

$$\hat{u}_{jt} = R_{jt} - R_{mt} \tag{1}$$

where $\hat{u}_{jt}$ referred to the 'residual return' of the stock, R_{mt} referred to the returns of the total market being considered and R_{jt} to the returns of the individual stock. They thus adjusted for market-related risk, but did not consider idiosyncratic risk factors. Since at every point t in time, the same market return, R_{mt}, was applicable to all firms, $\hat{u}_{jt}$ was equivalent to raw returns where relative stock performance for the purpose of portfolio formation was concerned.

Blitz et al. (2011) proposed the use of what they called "residual momentum" as an alternative to the above. Only returns not related to the firm's fundamental value considering risk and market movement as per the Fama-French three factor model (Fama & French, 1992) were taken into account:

$$r_{i,t}-r_t^f = \alpha_i + \beta_{1,i}\cdot(r_t^M-r_t^f) + \beta_{2,i}\cdot SMB_t + \beta_{3,i}\cdot HML_t + \varepsilon_{i,t} \quad (2)$$

where $r_{i,t}$ was the returns of firm i during month t, r^f_t represented the related risk-free return, r^M_t was the market return, α_i constituted the active return and $\varepsilon_{i,t}$ the unexplained returns. SMB_t and HML_t were the Fama-French factors for size and value respectively. $\beta_{1,i}$, $\beta_{2,i}$ and $\beta_{3,i}$ were the estimated factor loadings. $\varepsilon_{i,t}$ then reflected the residual returns on stock i in month t.

They found that following a momentum strategy with portfolios formed based on residual returns instead of total returns, significantly reduced exposure to dynamic risk factors, approximately halving volatility. In addition, residual or idiosyncratic momentum was closely aligned with total returns momentum in the short term, but residual momentum continued to generate positive returns for longer (Blitz et al., 2011).

Gutierrez and Pirinsky (2007) compared residual momentum to conventional momentum and found significant differences in the relative performance of these strategies. Similar to Blitz et al. (2011), they found strong reversal in conventional ("relative-return") momentum after the first year, while residual ("abnormal-return") momentum persisted for a long time. They also calculated residual momentum using $\varepsilon_{i,t}$ from equation 2, but they standardised the residual returns by dividing it with the standard deviation of these returns. However, they did note that qualitatively, the results were similar, regardless of this standardisation.

Gutierrez and Pirinsky (2007) additionally studied momentum based on α_i from equation 2, but found the results to be "qualitatively similar" (p. 17) to $\varepsilon_{i,t}$-based momentum. Grundy and Martin (2001) also applied α_i from equation 2 as a measure of stock-specific returns in calculating "the risk-adjusted profitability of a stock-specific return strategy" (p. 55) for comparison to a conventional momentum strategy. Alpha and the various betas were computed on a rolling 12-month basis. Ultimately, they found only marginal improvement for stock-specific return momentum over conventional momentum. Hühn and Scholz (2016) followed a similar method, referring to it as "alpha momentum". In contrast to

Grundy and Martin (2001), they found alpha momentum superior to conventional momentum, but only in the United States.

The use of alpha could become problematic, especially when shorter formation periods are investigated as the factor loadings could then become unduly exposed to momentum factors. The use of the residual allows for more flexibility in formation period length as the factor loadings are determined over a consistent period (as far as the data allows), arguably providing a less volatile asset pricing model. It is common in the literature for the determination of factor loadings to consider a stock's performance over the preceding 60 months, with 24 months seen as the minimum time period to obtain reliable results (Basiewicz & Auret, 2010; Fama & French, 1992).

2.2.2.2 Asset Pricing Model Employed

The determination of any residual return is highly dependent on the asset pricing model used and the magnitude of the relevant factor loadings. Employing the traditional CAPM, for example, would provide a simple, intuitive measure of excess or abnormal returns. Unfortunately, it has not performed well in a range of empirical tests (Fama & French, 2004).

Fama and French (1993) expanded on the traditional CAPM model by evaluating stock-return anomalies. They found both a size and value effect in the market and formulated a three factor risk model. Whilst there was debate over whether the book-to-market ratio (used to determine value) was a risk measure or mispricing measure and if it thus qualified as a rational risk model (Daniel & Titman, 1997; Lakonishok, Shleifer & Vishny, 1994), it has generally been accepted as an improvement over the CAPM and has been extensively used in literature.

In addition to the above, industry type has been found to be play a significant, although not constant, role in expected returns on the JSE. The JSE has been traditionally heavily weighted towards the resources industry and its structure has been described as dichotomous (Basiewicz & Auret, 2010; Beelders, 2003; Muller & Ward, 2013; Van Rensburg & Robertson, 2003). Internationally, industry specific risks have been noted to skew returns data and affect momentum profits (Moskowitz & Grinblatt, 1999).

This study ultimately used size and value factors supplemented with a type-of-industry variable in order to determine expected returns and, by extension, residual returns. These returns formed the basis for the construction of residual momentum portfolios.

Most asset pricing models have the limitation that the estimation of the relevant betas relies on past performance, while actual returns experience dynamic factor exposure. Betas are dependent on both firm and market historical movement, resulting in the residual momentum determination being affected by the beta estimation window. Regardless, residual momentum was found to be insensitive to different estimation period lengths as well as to the use of medians or means of regression estimates for factor loadings (Blitz et al., 2011; Grundy & Martin, 2001).

2.2.2.3 Differences between Residual and Conventional Momentum

A first significant difference between conventional and residual momentum recorded in the literature was that residual momentum profits were less volatile than that of a conventional momentum strategy (Blitz et al., 2011; Gutierrez & Pirinsky, 2007).

Second, conventional and residual momentum portfolios have been found to show similar results over the course of the first year after formation. Thereafter, however, conventional momentum reversed strongly while residual momentum continued for a longer time (Blitz et al., 2011; Gutierrez & Pirinsky, 2007).

While the results of especially conventional momentum have been acknowledged, there was little consensus on the fundamental drivers behind the phenomenon. Multiple theories abound and range from the cross-sectional variation in stock prices (Conrad & Kaul, 1998) to a rational risk-based explanation (Barr, 2015). However, the literature overwhelmingly favours behavioural finance as the cause behind markets not behaving efficiently. Behavioural factors support the notion that momentum and mean reversion is due in essence to markets initially under-reacting to a shift in the value of a security, then overreacting until finally the price reverts to its fundamental value (De Bondt & Thaler, 1985; Hong & Stein, 1999).

The differences in reversal patterns and volatility suggested that conventional momentum is linked to overreaction and residual momentum to under-reaction (Gutierrez & Pirinsky, 2007). The following sections provide a summary of pertinent and prominent theories behind the momentum phenomenon by means of which the results of the study are discussed in a later chapter.

2.2.2.4 Behavioural Explanations for Momentum

Mispricing of stocks often follows a pattern of over- and under-reactions of share prices to news. Barberis et al. (1998) explained these over- and under-reactions along the psychological constructs of conservatism and the representativeness heuristic. Representativeness refers to where investors view news and firm or industry performance as representative of that firm or industry and ignore the probability that it will revert to the mean at some point, leading to an overreaction in the share price. Also, due to conservatism, individuals are slow to change their beliefs when supplied with new evidence. This contributes to investor under-reaction to market news (Barberis et al., 1998).

This theory could conceivably explain both conventional and residual momentum. The returns of firms exposed to similar external risk factors are likely to show some level of co-movement, thereby increasing the chances of the representativeness heuristic playing a role in investor decisions and leading to overreaction. Due to conservatism, investors are simultaneously unlikely to react to news of idiosyncratic returns unrelated to market and risk factors, especially if these go against a trend in total returns. This could thus explain under-reaction to residual momentum.

Daniel et al. (1998) considered self-attribution and overconfidence biases to play a role in the anomalous market behaviour. Self-attribution bias refers to when an individual ascribes an event that confirms the validity of his actions to his own ability, but events that disconfirm it are ascribed to bad luck or external interference. Again investors react too slowly to news that goes against their prevailing opinion. This is closely correlated with the concept of cognitive dissonance (Antoniou et al., 2013).

Hong and Stein (1999) considered market under- and overreactions to originate from the effects of bounded rationality and the slow rate of news diffusion across the market. Investors tend to fall into one of two camps: newswatchers who only trade on future price expectations, and momentum traders who only react to past prices. Both groups are boundedly rational and operate according to their own philosophy. The diffusion rate of news across the market means that individual newstraders do not have access to all news at all times and prices tend to under-react. Momentum traders rely fully on past performance, meaning that they continue to buy even when a stock goes beyond its fundamental price, resulting in overreaction.

Similar to Barberis et al. (1998), Hong and Stein’s (1999) model above could also explain both momentum strategies under discussion. Momentum traders trade on conventional momentum only, allowing it to display the overreaction and mean reversion for which momentum is known. Newswatchers consider firm specific news, including news reflected in residual returns, but this is slow to permeate the market, resulting in the under-reaction behaviour of residual momentum.

Bikhchandani, Hirshleifer and Welch (1998) posited that systems, such as the stock market, are subject to informational cascades theory. A small amount of information is released to which the system reacts, which in turn, itself signals more information. Investors in the stock market could thus exhibit herd-like behaviour, thereby causing share prices to rise or fall beyond rational, fundamental levels. Other proponents of herding as an explanatory factor in stock market inefficiencies included Gutierrez and Kelley (2009).

2.2.2.5 Non-behavioural Explanations for Momentum

Conrad and Kaul (1998) and Dittmar, Kaul and Lei (2007) argued that the cross-sectional variation in stock prices could account for most momentum profits observed. Barr (2015) expanded on this by finding support for the rational explanation for momentum being due to cross-sectional variation in expected returns in winner/loser portfolios resulting from sorting by past returns and the risk implications of these portfolios.

This argument was of particular interest as the premise of residual momentum was built around reducing exposure to common risk factors at the portfolio formation stage. Resultantly, diversification in the portfolios could be higher and returns volatility may be lower. It must be noted that residual momentum's results would be dependent on which risk factors were addressed.

Another possibility is that momentum profits found in literature were due to industry factors common to stocks picked as winners/losers. Industry specific risks are not diversified away and thus skew the data (Moskowitz & Grinblatt, 1999). However, subsequent studies refuted industry factors as the sole explanation for momentum strategy profits (Grundy & Martin, 2001; Jegadeesh & Titman, 2011).

Gutierrez and Pirinsky (2007) linked momentum to the actions of institutional investors and the dynamics that agency theory imposes on their decision making. This phenomenon could arguably also be seen as a behavioural explanation for momentum as it is based on the boundedly rational behaviour of institutional investors.

2.2.2.6 Advantages offered by Residual Momentum

While momentum on the JSE has been extensively researched, residual momentum on the JSE appears to be an under-studied area of research. Hsieh and Hodnett (2011) described the use of "cumulative average residual returns" (p. 115). However, they followed the methodology of De Bondt and Thaler (1985), as described earlier, which was equivalent to calculating momentum from raw returns. Redford (2015) used cumulative average abnormal returns calculated using the CAPM in an event study investigating the short term market reaction to firm share buy-back announcements on the JSE. This related closely to the wider study of residual momentum, but was very narrow in scope.

One of the main aims of this study was therefore to add to the academic literature by testing whether the use of residual momentum on the JSE could lead to similar improvements over conventional momentum as found in other markets. Furthermore, the comparison of residual and conventional momentum provided the opportunity to investigate the applicability of the proposed theories explaining the phenomena.

Another benefit to investigating and using residual momentum is a resulting dataset that is less dependent on size, value and industry dynamic risk factors. The influence of investor sentiment on momentum can thus be better isolated, leading to greater insights into the drivers behind these anomalies.

Residual momentum's importance in real world applications was due to its reported reduced volatility and crash-risk. While momentum profits have shown remarkable profits for a number of years, it has been shown to be exposed to the risk of significant crashes, most notably when rebounding from major bear markets. A case in point is the fact that a conventional momentum strategy in the United States would have suffered losses of over 90 percent in 1932 and about 73 percent in 2009 (Barroso & Santa-Clara, 2015). This was related to the fact that during a market crash, the worst performing stocks were mostly high beta stocks and the best performing ones mostly low beta stocks. A market rebound then resulted in large gains in the shorted loser portfolio, without corresponding gains in the winner portfolio (Blitz et al., 2011; Daniel & Moskowitz, 2013). This is also applicable at industry level where concerted price movement within an industry can cause undue exposure to an industry in a momentum portfolio. The use of residual momentum attempts to limit exposure to high risk stocks and to reduce the homogeneity of stocks in a portfolio, thereby reducing volatility and decreasing the likelihood of a momentum crash during a sudden market recovery.

2.3 Investor Sentiment

Investor sentiment is defined as "a belief about future cash flows and investment risks that is not justified by the facts at hand" (Baker & Wurgler, 2007, p. 129) or it "represents the expectations of market participants relative to a norm" (Brown & Cliff, 2004, p. 2). It lies at the heart of behavioural finance theories and is often quoted as the source of a market's perceived inefficient behaviour.

Its effect on the market was based on two underlying assumptions:

Firstly, investors do not always behave rationally as they are subject to emotion. The perception of investors, especially less sophisticated and less knowledgeable ones, regarding the true value of a share is not always based on available evidence regarding expected future cash flows (Baker & Wurgler, 2007; Brown & Cliff, 2005). Furthermore, these retail investors' perceptions of risk and what is deemed acceptable risk is also subjective and is prone to change depending on their sentiment (Baker & Wurgler, 2007).

Secondly, while there is assumed to always be arbitrageurs and rational traders who will ensure a share price will return immediately to its fundamental value, it is also assumed that there are limits to arbitrage (Baker & Wurgler, 2007; Shleifer & Vishny, 1997). These include the fact that it is costly to bet against the prevailing sentiment. Maintaining a contrarian strategy in the face of long term growth in an industry or segment is difficult, even for institutional investors as they need to show consistent growth during frequent performance evaluations. If a period of optimism that leads to irrational pricing, or a 'bubble', is sustained for a noteworthy period of time, contrarian investors could easily be forced out of business (Baker & Wurgler, 2007; Brown & Cliff, 2005; Gutierrez & Pirinsky, 2007).

The result is that share prices increase (decrease), without any fundamental basis, in periods of excessive optimism (pessimism) due to greater (lesser) demand. Limits to arbitrage mean that the subsequent mispricing is not dissipated immediately. At a market aggregate level, investor sentiment is often used as a contrarian indicator predicting price reversals to the mean in the long run. If the prevailing sentiment is high (low), future market returns tend to be lower (higher) (Baker & Wurgler, 2007; Brown & Cliff, 2005).

Considering cross-sectional returns in the market, stocks that are difficult to value and stocks that are difficult to arbitrage will be more sensitive to sentiment as they are likelier to be mispriced by emotional investors and less likely to be arbitraged by rational investors respectively. Companies that are smaller, younger, more volatile, non-dividend paying and seen as growth stocks often satisfy both of these criteria simultaneously, making them vulnerable to sentiment fluctuations in the stock market (Baker & Wurgler, 2006; Dalika & Seetharam, 2015).

2.3.1 Sentiment in International Markets

Baker and Wurgler (2006) studied the effect of investor sentiment on the cross-section of stock returns on the NYSE. Their findings supported the theoretical assumptions that stocks that are difficult to value and arbitrage show greater sensitivity to the level of investor sentiment. Brown and Cliff (2004) found evidence that in the short run, markets affect sentiment, but sentiment only affects market returns in the long run.

Numerous other studies corroborated the above to varying degrees while investigating sentiment in different markets (Boubaker & Talbi, 2014; Li & Yeh, 2011), using different measures of sentiment (Baker & Wurgler, 2007; Neal & Wheatley, 1998; Schmeling, 2009) and testing the reaction of the market to different events (Mian & Sankaraguruswamy, 2012; Rosen, 2006).

2.3.2 Sentiment on the JSE

The JSE was found to behave similarly to the NYSE with regard to investor sentiment. Returns on small, young, high volatility and growth stocks were low subsequent to periods of positive sentiment and vice versa (Dalika & Seetharam, 2015).

A recent study (Solanki & Seetharam, 2014) found investor sentiment as approximated through a consumer confidence index to indicate future market performance. Consumer confidence was found to be a leading indicator of JSE market performance.

Hodnett (2014) linked recent value-growth spreads to investor sentiment on the JSE and suggested that this could be used as an indicator for future returns. An earlier study found prices on the JSE to be sensitive to macroeconomic variables similar to those used in approximating investor sentiment (Van Rensburg, 1995).

Mackinnon and Kruger (2014) investigated factors that affected analysts' recommendations towards shares on the JSE and found that investor sentiment, proxied by a business confidence index, was not a significant factor.

2.3.3 Explanations for Investor Sentiment's Effect on the Market

The effects of investor sentiment were explained by means of many of the same behavioural theories put forward for momentum. The difference being that investor sentiment affects the human emotional, psychological or cognitive effects present in retail investors while momentum results from markets responding in an inefficient manner due to the presence of these factors (Mian & Sankaraguruswamy, 2012). The following sections provide a non-exhaustive list of viable theories behind the impact of investor sentiment on financial markets against which to assess the results of this study.

2.3.3.1 Non-rational Investor Behaviour

As an example, in times of positive investor sentiment, investors could be more prone to Daniel et al.'s (1998) overconfidence and self-attribution biases. Overconfidence is presumed to be more pronounced in times of positive sentiment, leading to share price overreaction. Retail investors are also assumed to react more slowly to bad news in times of positive sentiment, due to both the overconfidence and self-attribution biases.

Antoniou et al. (2013) ascribed this to cognitive dissonance where, building on the work of Hong and Stein (1999), they speculated that 'newswatchers' react more slowly to news that contradicts their prevailing sentiment, slowing the diffusion of news across the market. Furthermore, investors' conservatism and anchoring biases (Barberis et al., 1998) result in a slow change of beliefs (sentiment) in the face of new evidence. Mian and Sankaraguruswamy (2012), in a study investigating the reaction of stock prices to earnings announcements, found stock prices to be more sensitive to good (bad) earnings news during periods of optimism (pessimism).

Apart from directly affecting the share price through market supply and demand mechanisms, sentiment could also affect company managers' investment decisions thereby affecting future returns and profitability (Barberis & Thaler, 2003, p. 1106).

2.3.3.2 Limits to Arbitrage

Limits to arbitrage could take various forms. Fundamental risk prevents arbitrageurs from taking an excessive position in any one stock. Additionally, implementation costs ensure arbitrageurs only pursue trades with sufficient profit potential. The implementation costs associated with shorting a stock can often be quite high. A further limitation to shorting is that certain markets or fund types do not allow short selling (Barberis & Thaler, 2003, p. 1057; Shleifer & Vishny, 1997).

Noise trader risk means that there is no way for the arbitrageur to know the magnitude of stock mispricing by noise traders or the duration of the mispricing. While an arbitrageur might be convinced of the mispricing of a particular stock, this price divergence could be sustained for a lengthy period of time. Risk aversion or capital constraints could then force the arbitrageur to abandon his position at a significant loss (Barberis & Thaler, 2003, p.

1057; Shleifer & Vishny, 1997). Small, young, hard-to-value and illiquid stocks all compound the above risks and increase their limits to arbitrage (Baker & Wurgler, 2006).

Constraints imposed on active fund managers relating to short sale constraints and fund weighting limitations in a concentrated investment environment such as the JSE exacerbates general limits to arbitrage (Raubenheimer, 2012).

It is unlikely that any one of the above mentioned theories constitutes the sole explanation for the effect of sentiment in stock markets as human investors are too complex to be modelled by these variables independently. Rather, an aggregate of the above mentioned models could contribute to the effects of sentiment on market prices and volatility.

2.4 Investor Sentiment and Momentum

The phenomena of investor sentiment and momentum are both closely related to stock markets' tendency to under- and overreact to market-related news. Both are mostly explained at the hands of behavioural finance theories. Investor sentiment is expected to influence the extent to which the biases of investors cause mispricing, while momentum is explained as the result of market under- and overreaction due to these investor biases and bounded rationality. One would therefore expect momentum effects to be more pronounced in periods with elevated (positive or negative) sentiment levels.

Stambaugh et al. (2012) found significant differences in the returns of the shorted conventional momentum portfolio following high and low levels of sentiment. However, the returns of a zero-investment momentum strategy did not show significant differences based on investor sentiment. Lemmon and Portniaguina (2006) also failed to find significant sentiment effects on momentum profits.

Antoniou et al. (2013) studied the effect of investor sentiment on the profitability of momentum trading strategies on the NYSE. They found support for the notion that momentum profits increase when sentiment is increased. They hypothesised that this was due to cognitive dissonance slowing the reaction time of the market to news that contradicts prevailing sentiment, thus resulting in an increased and extended mispricing phase.

However, they also found that momentum profits were only profitable following optimistic periods. They ascribed the one-sidedness of the effect due to short-selling constraints limiting the power of arbitrageurs to arbitrage away mispricing of losers during optimistic periods.

This study was most closely comparable with that of Antoniou et al. (2013) and tested the above mentioned results in the context of the Johannesburg Stock Exchange. However, the primary focus was the investigation of the effect of investor sentiment on residual momentum. Residual momentum was expected to lower the exposure of the momentum strategy to market risks, including size and value factors (Blitz et al., 2011). As sentiment has been found to have a cross-sectional effect on the market, specifically on size and value factors, the effect of sentiment on residual momentum was likely to be markedly different to that of conventional momentum.

The investigation into the link between sentiment and momentum held various practical and academic implications. Practically, traders and investors constantly consider ways to 'beat the market', a prospect which has become exceedingly difficult in recent years. Understanding the link between sentiment and momentum and incorporating the results into a trading strategy could allow for improved returns.

Academically, the intersection between sentiment and momentum provided the opportunity to test the implications and applicability of major behavioural finance theories on the JSE as both concepts were often explained by means of these theories. Considering the extent to which residual momentum appeared to be affected by investor sentiment also advanced the literature on both of these concepts.

3 Research Questions and Hypotheses

A major contribution to the literature made by the study was the investigation of residual momentum on the JSE and whether the improvement in risk-adjusted returns of residual momentum over conventional raw price momentum, as observed by Blitz et al. (2011), was also applicable to the JSE. This led to the first research question:

Q1) Did a momentum strategy that employed residual momentum provide greater risk-adjusted profits than a conventional momentum strategy on the JSE?

These strategies were compared using various different metrics of risk-adjustment returns. The first considered the total cumulative returns of the two strategies. The resulting null hypothesis statement was:

$$\mathbf{H_0:} \qquad \mathbf{R_{CMOM} - R_{RMOM} <> 0}$$

where R_{RMOM} referred to the cumulative return of residual momentum strategy followed over the sample period and R_{CMOM} referred to the cumulative return of a conventional momentum strategy followed over the same period. *Note that this and other hypotheses statements provided in this chapter acted as main or overarching hypotheses. The analysis section (Chapter 5) detailed the specific hypotheses used for each test.*

Secondly, cross-sectional comparisons of the returns to residual and conventional momentum strategies as well as their associated winner and loser portfolios were conducted.

$$\mathbf{H_0:} \qquad \mathbf{\tilde{R}_{CMOM} - \tilde{R}_{RMOM} <> 0}$$

where $\tilde{R}_{RMOM}$ referred to the median returns or the distribution of returns of the strategies over the time period studied.

Thirdly, the Sharpe ratio, a commonly-used measure of risk-adjusted returns, of the two strategies were compared, leading to another main hypothesis statement:

$$\mathbf{H_0:} \qquad \mathbf{SR_{CMOM} - SR_{RMOM} <= 0}$$

where SR_{RMOM} referred to the Sharpe ratio of the residual momentum strategy and SR_{CMOM} referred to the Sharpe ratio of the conventional momentum strategy. The Sharpe ratio was defined as mean excess returns divided by the standard deviation of the associated excess returns (Sharpe, 1994). It was assumed that the standard deviation, a measure of volatility, was indicative of the risk associated with the strategies.

A further aim of the research was to observe and describe the effect of investor sentiment on momentum in the market. How this effect might differ between residual and conventional momentum was also of interest. The second research question was therefore:

Q2) Was there any observable evidence of an investor sentiment-based effect on residual and conventional momentum profits on the JSE?

The level of investor sentiment during the momentum portfolio formation period was classified as pessimistic, neutral or optimistic. The returns of the momentum strategies across these different periods were then studied to determine if their excess profits were significantly different between states. To test whether the effect observed in previous studies were due to the employed momentum measures' exposure to risk factors, both residual as well as conventional momentum strategies were examined. From this followed two further primary hypotheses statements:

$$\mathbf{H_0:} \qquad \mathbf{R_{RMOM,OPT} = R_{RMOM,NTR} = R_{RMOM,PES}}$$

and

$$\mathbf{H_0:} \qquad \mathbf{R_{CMOM,OPT} = R_{CMOM,NTR} = R_{CMOM,PES}}$$

where the suffixes OPT, NTR and PES referred to optimistic, neutral and pessimistic periods of investor sentiment as observed during the portfolio formation phase of the residual momentum and conventional momentum strategies (suffix RMOM and CMOM respectively).

4 Research Methodology

4.1 Research Design

The research consisted of two main parts. The first part determined how a residual momentum strategy compared to a conventional momentum strategy on the JSE. The second part investigated the influence of investor sentiment on residual and conventional momentum strategies on the JSE.

Both parts of the study entailed a quantitative, deductive, explanatory, quasi-experimental analysis. A quantitative methodology was used as the financial data associated with stock markets lent itself to this. The research was essentially an empirical finance study and thus quantitative by nature.

The concepts studied such as investor sentiment, momentum and market risk factors were all well-defined and were thus deduced from the literature and did not emerge during the course of the study, making the deductive approach appropriate (Saunders & Lewis, 2012). This study was explanatory as it went beyond being merely descriptive, but rather built on the available literature and added to the explanations behind the above mentioned market phenomena.

A quasi-experimental approach was followed as random unit assignment was not possible. The units of analysis, i.e. stocks listed on the JSE, were not amenable to traditional experimental analysis. Due to the lack of randomisation, more thought, logic and consideration had to be given to attempt to eliminate alternative causes for the results found (Shadish, Cook & Campbell, 2002). However, the quasi-experimental approach held the following advantages applicable to this study:

- The external validity of quasi-experimental designs could exceed that of traditional randomised experimental analysis as field data was used rather than simulated laboratory data (Jensen, Fast, Taylor & Maier, 2008).
- It also required no primary data gathering and inferences could be drawn from secondary data sets (Jensen et al., 2008). This was a significant advantage, considering the time constraints imposed on the research project.

4.2 Unit of Analysis

The units of analysis were stocks listed on the Johannesburg Stock Exchange throughout the sample period.

4.3 Population

Towards the construction of momentum portfolios, the population was similar to that of Muller and Ward (2013) and only considered the top 160 shares in terms of market capitalisation listed on the JSE, roughly those that were included in the All Share Index. Shares outside of this were assumed to be too small and illiquid for institutional investors to consider. In terms of market value, the top 160 shares represented approximately 99 percent of the value of the JSE over the period sampled. In using only these shares, issues such as an overexposure to illiquid and small shares that could have skewed the data were prevented. This was especially important on the JSE with its large number of very small shares.

4.4 Sampling

Restricting the population of the study to only the 160 largest shares on the JSE allowed the entire population to be included in the study.

To enable the calculation of residual returns for a specific firm, a minimum of two years' worth of data were required to firstly determine reliable betas (Basiewicz & Auret, 2010; Ward & Muller, 2012). Blitz et al. (2011) found beta estimation windows between 24 and 60 months to not materially affect the results of their study into residual momentum. Firms therefore had to have been listed for at least two years to be included in the population used for the selection of residual momentum portfolios. This limitation was not imposed on the construction of conventional momentum portfolios.

Data were available from early 1987 until June 2016. Due to the requirement of two years' worth of firm level data for the calculation of associated residual returns, the final sampling period was from 1 January 1989 until 30 June 2016, with the first portfolios' formation point being 31 March 1989. This resulted in 327 months or 109 quarters of returns data.

4.5 Research Question 1 Constructs: Momentum

4.5.1 Portfolios

The momentum strategy employed was similar to that used in other prominent studies on momentum (Antoniou et al., 2013; Daniel & Moskowitz, 2013; Jegadeesh & Titman, 1993). This entailed the construction and analysis of portfolios to manage the volatility inherent in the data.

Five equal-weighted quintile (Fraser & Page, 2000; Muller & Ward, 2013) stock portfolios were created by ranking stocks on a variable indicative of past performance (see sections 4.5.3 and 4.5.4). A zero-investment strategy was followed. This entailed taking a long position on the portfolio of top ranked stocks or 'winners' and an equal short position on the portfolio containing the lowest ranked stocks or 'losers'. The returns of the winner and loser portfolios were then calculated as the total returns of the constituent firms over the holding period, with the zero-investment portfolios' returns consisting of the difference between the returns of the winner and loser portfolios.

As per Muller and Ward (2013), non-overlapping portfolios were constructed. Every quarter's returns were therefore related to a distinct set of portfolios formed at the start of the quarter. In order to determine the cumulative performance of each portfolio and style over the time period studied, each portfolio was initially set at a base of 1.0 which was adjusted on a cumulative basis from daily returns. The cumulative value of each portfolio was retained at the end of each quarter during rebalancing when portfolio constituents were modified, based on new ranks from an updated sample of the largest 160 stocks.

4.5.2 Portfolio Formation and Holding Periods

The literature was not clear on the optimal formation and holding periods for momentum strategies. However, a number of studies, both local and international, applied momentum strategies with a formation period of 12 months (Asness et al., 2013; Fama & French, 1996; Jegadeesh & Titman, 1993; Muller & Ward, 2013) and a holding period of one, three or six months (Blitz et al., 2011; Daniel & Moskowitz, 2013; Muller & Ward, 2013).

However, most of these studies were based on conventional momentum and not residual momentum. As a major part of the study concerned the performance of residual momentum on the JSE, various formation and holding periods were investigated to determine the optimal periods for use in a residual momentum strategy. The results were summarised in section 5.1.2. Based on these results and in order to simplify the implementation of the momentum strategies, formation periods of twelve months and holding periods of three months were used in this study for both residual momentum as well as conventional momentum.

The identical formation and holding periods also allowed transaction costs related to quarterly portfolio rebalancing to be ignored in this study on the grounds that it would be approximately the same across the two momentum strategies (Muller & Ward, 2013).

It was common in the literature (Daniel & Moskowitz, 2013; Fama & French, 1996; Jegadeesh & Titman, 1993) for the authors to disregard stock returns during the most recent month when determining a stock's level of momentum. This was done in order to mitigate distortions due to short term momentum reversals as documented by Jegadeesh (1990) and Lehmann (1990). However, no short term reversal was evident in the results provided in section 5.1.2, and thus, to prevent unnecessary methodological complications, the most recent month's returns were included in the formation period.

4.5.3 Conventional Momentum

The difference between residual and conventional momentum lay in the variable used to determine past performance. The conventional momentum strategy entailed ranking stocks based on the total returns of each stock during the formation period and constructing five equally weighted portfolios based on these rankings. The realised returns consisted of the total returns of the firms in the respective portfolios over the holding period.

4.5.4 Residual Momentum

The residual momentum of a firm was determined from its total excess returns, not explained by risk factors, over the formation period. This study defined excess returns as per Equation 3 (page 30). Stocks were ranked according to their total excess returns over the formation period and sorted into five equally weighted portfolios. The realised returns considered the total returns of the firms in the respective residual momentum portfolios over the holding period.

4.5.5 Asset Pricing Model

The residual momentum strategy was determined using characteristic portfolios constructed from factors similar to that used by Fama and French (1992), as well as an additional factor related to the type of industry in which the firm operated.

Muller and Ward's StyleEngine was used to determine twelve characteristic portfolios created from an independent three-way sort of three size portfolios on two value portfolios and two industry portfolios (Muller & Ward, 2013) consisting of the top 160 stocks on the JSE in terms of market capitalisation.

Precedence for the exclusion of small and illiquid stocks in the calculation of the asset pricing model and associated elementary portfolio break points can be found in Fama and French (1992), who considered only NYSE stocks in determining the break points for the creation of their elementary portfolios. This was done in order prevent a situation where "…most portfolios would include only small stocks…" (p. 430). For the same reason, Basiewicz and Auret (2009) used only the top 200 stocks based on share liquidity on the JSE to determine the elementary portfolio break points during their investigation of the Fama-French three factor model on the JSE. They also applied a size and liquidity filter to the stocks. This StyleEngine's use of only the top 160 stocks was therefore consistent with previous research. The top 160 stocks covered 99 percent of the market capitalisation and liquidity, avoiding exposure to very small and extremely illiquid shares without significantly affecting results.

This study used market capitalisation, determined from the share price multiplied by the number of shares outstanding, to define firm size. The break points for size were equivalent to the JSE indices for large, medium and small cap stocks, with the largest 40 seen as large, 41 to 100 seen as medium and 101 to 160 seen as small.

Value was proxied by the ubiquitous price-earnings (PE) ratio. The median PE ratio was used as the break point, with firms with PE ratios smaller than this seen as value stocks and those with greater PE ratios seen as growth stocks.

Finally, firms were classified as either resource or non-resource stocks based on the JSE industry classification benchmark.

The three-way sort resulted in the twelve characteristic portfolios presented in Table 1. The characteristic portfolios were reformed annually, similar to Fama and French (1992) and Basiewicz and Auret's (2009) factor reformation. It has been found that more frequent characteristic portfolio rebalancing could confound the size and value factors with the short term reversals noted by Jegadeesh (1990).

Table 1: Characteristic Portfolios

Size	Value	Industry	Name
Large	Value	Resources	**LVR**
		Non-resources	**LVN**
	Growth	Resources	**LGR**
		Non-resources	**LGN**
Medium	Value	Resources	**MVR**
		Non-resources	**MVN**
	Growth	Resources	**MGR**
		Non-resources	**MGN**
Small	Value	Resources	**SVR**
		Non-resources	**SVN**
	Growth	Resources	**SGR**
		Non-resources	**SGN**

This resulted in an asset pricing model assuming the following equation:

$$r_{i,t} = \alpha_i + \beta_{1,i}\cdot(LVR_t) + \beta_{2,i}\cdot(LVN_t) + \beta_{3,i}\cdot(LGR_t) + \beta_{4,i}\cdot(LGN_t) + \beta_{5,i}\cdot(MVR_t) + \beta_{6,i}\cdot(MVN_t) + \beta_{7,i}\cdot(MGR_t) + \beta_{8,i}\cdot(MGN_t) + \beta_{9,i}\cdot(SVR_t) + \beta_{10,i}\cdot(SVN_t) + \beta_{11,i}\cdot(SGR_t) + \beta_{12,i}\cdot(SGN_t) + \mathcal{E}_{i,t} \quad (3)$$

where $r_{i,t}$ referred to the total returns of stock i during time period t. LVR_t, LVN_t up to SGN_t referred to the returns on the respective characteristic portfolios during the corresponding time period. $\beta_{1,i}$, $\beta_{2,i}$ up to $\beta_{12,i}$ were the estimated factor loadings towards each characteristic portfolio and α_i was the intercept of the equation. $\mathcal{E}_{i,t}$ then reflected the residual returns on stock i during time period t.

Betas were determined using returns over the previous 24 to 60 months, depending on data availability. The 60 month rolling window for beta estimation was common in the literature to ensure sufficient stability in the factor loading (Basiewicz & Auret, 2009; Fama & Macbeth, 1973; Nieto, Orbe & Zarraga, 2014), while 24 months was seen as the minimum period for reliable values (Basiewicz & Auret, 2010; Ward & Muller, 2012). Betas were based on the relationship between the daily returns of the firm and that of the characteristic portfolios. Betas were updated quarterly, prior to the rebalancing of the momentum portfolios.

4.6 Research Question 2 Constructs: Investor Sentiment

Quantifying investor sentiment proved to be a significant challenge for any academic research into this phenomenon. Traditional methods followed either a direct approach whereby potential investors respond to queries and questionnaires regarding their prevailing sentiment or an indirect, top-down approach where a number of market variables are used as proxies for aggregate investor sentiment (Baker & Wurgler, 2006).

4.6.1 Consumer Confidence Indicator

A commercially available consumer confidence indicator was used in this study, namely the First National Bank / Bureau of Economic Research Consumer Confidence Index (FNB/BER CCI, henceforth CCI). Consumer confidence indicators are normally survey based, polling a random selection of consumers on their perceptions of the market and the state of the economy (Kershoff, 2000). Survey based indicators suffer from limitations inherent in such studies such as sampling concerns, interviewer bias, acquiescence bias and others (Saunders & Lewis, 2012). These studies are also updated less regularly than market related indicators. Finally, the survey might not accurately capture the sentiment of investors as the population of the survey (South African households) does not accurately match the population of investors on the JSE which includes many foreigners and is skewed towards institutional fund managers.

However, despite the limitations, consumer confidence has been found to be a viable investor sentiment proxy (Qiu & Welch, 2006). It has also been used in a number of prominent studies as a proxy for investor sentiment and its influence on the market (Antoniou et al., 2013; Lemmon & Portniaguina, 2006; Schmeling, 2009). On the JSE specifically, Solanki and Seetharam (2014) have found consumer confidence as measured by the FNB/BER CCI to be a leading indicator of market performance. It offered advantages over market based indicators as it was a more direct measure of sentiment and required little justification of its face validity for acting as a sentiment proxy (Boubaker & Talbi, 2014). The sampling and surveying methodology was also meticulously documented and followed, negating some of the concerns regarding sampling biases.

4.6.2 Macroeconomic Variables

The CCI indicator included sentiment effects that may be due to fundamental economic factors. In order to isolate only excess optimism or pessimism, the sentiment indicator was regressed against variables indicative of macroeconomic and business cycle trends. The results of the regression equation were then assumed to indicate sentiment due to fundamental factors while the residual of the regression indicated only excess sentiment not justified by fundamentals (Antoniou et al., 2013; Baker & Wurgler, 2006; Lemmon & Portniaguina, 2006). The latter matched the definition of sentiment as "a belief…not justified by the facts at hand" (Baker & Wurgler, 2007, p. 129).

Previous studies generally considered between three and nine macroeconomic variables (Baker & Wurgler, 2007; Dalika & Seetharam, 2015; Lemmon & Portniaguina, 2006; Mian & Sankaraguruswamy, 2012) against which to orthogonalise the sentiment indicator. This report considered five variables based on previous research as well as availability of data for the South African market across the time series studied. The variables used by Dalika and Seetharam (2015) were included, namely inflation, employment growth and industrial production growth. Additional factors were identified as per Lemmon and Portniaguina (2006), and included gross domestic product (GDP) growth and the yield on Treasury notes.

Inflation: Inflation data were obtained from the month-on-month consumer price index inflation data, as published by Statistics South Africa.

Employment Growth: Employment growth was determined from quarterly employment data retrieved from the Euromonitor International database. This represented the unemployed as a percentage of the economically active population in the country. Quarterly employment growth was defined as the change in the unemployment rate. A higher figure therefore meant higher unemployment and was expected to be associated with lower sentiment.

Industrial Production Growth: Industrial production data was proxied by the database "Total Volume of Production Indices" obtained from McGregor BFA. Quarterly industrial production growth was defined as the logarithmic growth in this index.

$$\text{Quarterly Industrial Production Growth (qtr)} = \ln(IP_{qtr}) - \ln(IP_{qtr-1})$$

where IP_{qtr} denotes the total industrial production volume for the current quarter. Monthly industrial production growth, IPG, was determined from a linear interpolation of quarterly growth figures.

Yield on Treasury Bills: Short term bond yields were obtained from the South African Reserve Bank. Monthly yield data, YTB, was defined as the average daily quoted rate during the month.

GDP Growth: Quarterly updated, seasonally adjusted GDP at constant prices, calculated from the expenditure approach to GDP, was obtained from McGregor BFA. Quarterly GDP growth was defined as the logarithmic growth in GDP.

$$\text{Quarterly GDP Growth (qtr)} = \ln(GDP_{qtr}) - \ln(GDP_{qtr-1})$$

where GDP denoted the South African GDP at current prices and qtr indicates the current quarter. Linear interpolation of quarterly GDP growth was used to approximate monthly GDP growth.

The CCI data series was orthogonalised against the five macroeconomic variables discussed above, with the residual from the regression taken as a cleaner proxy for investor sentiment. High autocorrelation was an inherent feature of the data as predicted by Brown and Cliff (2005), but was not expected to pose validity problems based on the manner and choice of statistical tests in which this variable was used.

The effect of investor sentiment on momentum on the JSE was analysed using the derived investor sentiment proxy, with the results validated through an additional analysis using the raw CCI.

4.7 Data Collection

4.7.1 Share Price and Firm Level Financial Data

The StyleEngine of Muller and Ward (2016) was used, with the owners' permission, in order to facilitate the analysis of the data. This included the use of Muller and Ward's historical database, compiled from McGregor BFA and the JSE Bulletin, and their proprietary software. The database contained, amongst other variables, the following required data for firms listed on the JSE:

Table 2: Financial Data Required

Share price	Used in calculating returns for momentum strategies and in determining the market capitalisation of the stock
Dividends paid	Dividends were included when calculating returns
Shares outstanding	Used in conjunction with share price to calculate market equity which in turn was used to the determine the size factor
Earnings	Used in conjunction with share price to calculate the value factor
Industry	The type of industry was also used as a factor in the pricing model adopted in the study

The database included new listings and delisted companies on a quarterly basis to prevent survivorship bias. It also included backward adjustments made for share splits, consolidations or name changes. Dividends were included as part of total returns as this formed a significant portion of total returns. Daily share price returns in excess of 40 percent either upwards or downwards were excluded as these were deemed data errors.

Financial data in the database was lagged for three months to prevent a look-ahead bias arising from the fact that firms can release audited financial data only after the financial year-end, resulting in this formation generally being not included in share prices at the time. The JSE allows up to three months for audited financial statements to be released.

4.7.2 Investor Sentiment Data

Investor sentiment was determined from the residuals of an ordinary least squares regression of the FNB/BER Consumer Confidence Index (CCI) on various macroeconomic variables.

The CCI is a quarterly updated survey based index. It is derived from personal interviews conducted with an area-stratified probability sample of 2500 households representing 92 percent of urban adults and 53 percent of the total South African adult population. The questionnaire and interviewers were selected to mitigate the impact of common survey biases as far as is practical. The simple questionnaire polls respondents on their perceptions of the general macroeconomic conditions and their own household's financial conditions over the next 12 months (Kershoff, 2000).

A net balance figure is derived from the difference in percentage of respondents expecting improvements and those expecting a decline, based on the answers to three questions relating to the consumer's perception of near term economic conditions:

1. How do you expect the general economic position in South Africa to develop during the next 12 months?
2. How do you expect the financial position in your household to develop in the next 12 months?
3. What is your opinion of the suitability of the present time for the purchase of domestic appliances such as furniture, washing machines, refrigerators, etc.?

Questions 1 and 2 are answered on a four factor point Likert scale and question 3 on a three point Likert scale (Kershoff, 2000).

As indicated in section 4.6.2, macroeconomic indicators were obtained from databases of various organisations, including Statistics South Africa, the South African Reserve Bank, Euromonitor International and McGregor BFA.

4.8 Analysis

Muller and Ward's (2013) StyleEngine with its associated database and proprietary software was used in order to facilitate the analyses. In particular, this software allowed for the formulation of portfolios based on either residual returns or total returns, where the formation or look-back period as well as the holding period could be varied.

4.8.1 Analyses towards Research Question One

Part one of the study included the first three main hypotheses comparing the cumulative and risk-adjusted returns of residual and conventional momentum strategies. All detailed hypotheses in the study were investigated using a significance level of 0.05.

To begin with, the viability of residual momentum as an investment style was evaluated through the application of statistical tests for significant difference comparing the mean returns of the five quintile residual momentum portfolios. A graphical time-series approach (described below) was also employed in order to further assess the historical performance of the residual momentum portfolios on the JSE.

The first main hypothesis concerned the comparison of the performance of residual and conventional momentum strategies based on cumulative returns. Cumulative returns provided a risk adjusted measure of returns as losses reduced the base of subsequent returns. A graphical approach similar to that of Muller and Ward (2013) was followed. The accumulated returns of the strategies were plotted on a time-series graph and inferences were made from the angle and consistency of the gradients in order to evaluate the hypothesis.

To allow for comparison with other studies regarding the differences in performance and volatility of the two strategies, the more traditional approach (Baker & Wurgler, 2006; Blitz et al., 2011; Jegadeesh & Titman, 1993; Stambaugh et al., 2012) of inferential statistical tests for significant differences between mean or median portfolio returns was also applied. Each strategy's top portfolio, bottom portfolio and zero-investment portfolio's performance was analysed. The above-mentioned tests for differences were supplementary and, due to the perceived methodological weakness (Muller & Ward, 2013) of these tests, the results of the graphical time-series approach took precedence in the interpretation of the results.

Finally, the strategies' Sharpe ratios were assessed, combining measures of profitability and volatility. Unconditional ex-post Sharpe ratios, determined from annualised returns and volatility, were computed and compared for the residual momentum and conventional momentum strategies as per Sharpe (1994):

$$SR = \frac{\bar{D}}{\sigma_D} \qquad (4)$$

Sharpe (1994) defined the ratio named after him to exclusively measure the performance of a "differential return" (p. 50) or a zero-investment strategy. Two different sets of Sharpe ratios were therefore calculated and discussed. The first set compared the returns of the respective momentum strategies' zero-investment portfolios. The term $\bar{D}$ in equation 4 referred to the mean annual returns of a zero-investment portfolio with σ_D referring to the associated standard deviation.

The second set compared the ratios of long only investment strategies investing in the winner portfolios of the momentum strategy as well as in the All Share Index. To satisfy the differential return requirement, only excess returns were considered in this particular analysis, with excess returns defined as total portfolio returns minus the risk free rate. Thus equation 4 was used, but with D referring to R_p – R_f, where R_p referred to the portfolio's returns and R_f to the risk free rate. The risk free rate was based on the yield on 91-day South African Treasury bills.

The returns and volatility for both sets of ratios calculated were based on monthly returns data which was subsequently annualised prior to being used in the Sharpe ratio calculations (Sharpe, 1994).

4.8.2 Analyses towards Research Question Two

The second part of the study investigated whether the level of investor sentiment affected the profits from residual and conventional momentum strategies. Inferential statistical analyses were applied comparing the returns of residual momentum and conventional momentum's respective winner, loser and zero-investment portfolios, based on the state of investor sentiment during the formation period. The use of the sentiment during formation periods effectively meant the investigation of returns based on a lagged sentiment predictor variable. The reasons for this were three-fold:

- It allowed for the practical application of the results of the study on real-world investment strategies as this level of investor sentiment would be known at or about the time of investment decision making.
- Solanki and Seetheram (2014) identified the CCI as a leading indicator of financial market performance in South Africa as proxied by the All Share Index. They found little evidence of a contemporaneous effect.
- It followed the work of international authors such as Antoniou et al. (2013), Stambaugh et al. (2012) and Cooper et al. (2004), amongst others, in using a

lagged investor sentiment variable when investigating the effect of sentiment on returns. However, these authors typically used monthly sentiment variables and compared the returns of overlapping portfolios formed over a number of months.

The primary investor sentiment proxy used for analysis in this report was the excess sentiment as determined from the regression of the CCI on the identified macro-economic variables. However, the tests were repeated using the unmodified CCI to verify whether the findings reported were not primarily due to the methodology followed to determine the sentiment proxy.

The monthly level of investor sentiment was determined as per section 4.6. To define the state of investor sentiment during a portfolio's formation period, a weighted measure of sentiment during the quarter just prior to formation was calculated from the following formula as per Antoniou et al. (2013):

$$WAFIS_t = \frac{(3 * IS_t + 2 * IS_{t-1} + IS_{t-2})}{6} \quad (5)$$

where $WAFIS_t$ referred to the weighted average level of investor sentiment during the formation period of a portfolio constructed at time t, IS referred to the level of investor sentiment at the time denoted by the subscript with t in monthly units. This ensured that greater weight was placed on the more recent levels of sentiment. More recent sentiment was expected to have a greater effect on the level of stock mispricing at portfolio formation.

Sentiment level cut-off or break points for the designation of optimistic, neutral and pessimistic periods had little precedence in the literature and required an element of judgement. Antoniou et al. (2013) used the 30th and 70th percentile as break points in their primary analysis. Sentiment periods in the top 30 percent over the time period studied were classified as optimistic and those in the bottom 30 percent as pessimistic, with the remainder being neutral. However, they used overlapping monthly data and required all associated formation periods to be optimistic (pessimistic) before classifying the formation period associated with specific returns obtained as being optimistic (pessimistic). This reduced the number of extreme investor sentiment periods recorded. It was therefore considered prudent to use as break points in the primary statistical analysis the 20th and 80th percentiles of formation period quarters ranked on the level of weighted average investor sentiment. Supplementary to this, cases with the top and bottom break points at the 15th and 85th percentiles and 30th and 70th percentiles respectively were also tested in order to verify the robustness of the results to the investor sentiment classification method.

A major methodological difference to the analysis employed by Antoniou at al. (2013) resided in the format of the data used. They used monthly returns as opposed to the quarterly returns used in this study to observe differences in returns across sentiment states. The use of quarterly returns was deemed a more appropriate measure for this study to investigate the effect of investor sentiment during the formation period on momentum returns as portfolios were only rebalanced on a non-overlapping, quarterly basis. Furthermore, three of the components used to determine the level of investor sentiment proxy used in this study, namely CCI, GDP growth and employment growth were quarterly published variables. Determining quarterly sentiment states therefore reduced the reliance on approximated interceding monthly sentiment values. Finally, the use of quarterly data largely eliminated the problems associated with auto-collinearity common in the analysis of time-series share returns data (Akgiray, 1989; Fama, 1965).

Due to the methodological differences stated above, Antoniou et al.'s (2013) results included the effect of investor sentiment well into the investment holding periods, which this study did not. The contemporaneous effect of investor sentiment on quarterly momentum returns was therefore also investigated. This test was conducted purely for academic interest, based on the above, as the results of this test held little practical application due to the required knowledge of future investor sentiment levels.

An arithmetic average value of sentiment during the three month holding period was calculated:

$$AHIS_t = \frac{(IS_{t+3} + IS_{t+2} + IS_{t+1})}{3} \tag{6}$$

Holding period sentiment states were determined in a similar manner as described above for formation period sentiment. The returns during each month of the holding were equally important, making the use of the arithmetic means in classifying holding period investor sentiment states applicable.

Excess returns, compensated for fundamental business cycle effects, were used in the study, by subtracting the returns on a risk-free investment from the total returns of each long-only portfolio. The risk-free rate was determined from the yield on 91-day Treasury bills as published by the South African Reserve Bank. Note that the zero-investment strategies of each portfolio already provided measures of relative returns with fundamental business cycle effects assumed to be present on both the long and short sides of the portfolio. The total returns of the zero-investment strategies were therefore seen as excess returns and no adjustments were required on these portfolios.

In order to test whether momentum profits from portfolios formed in different sentiment states were significant, the excess returns of the various portfolios were linearly regressed, with no intercept, on dummy variables for each of the three defined sentiment states: optimistic, neutral and pessimistic.

An additional regression was conducted for each portfolio, regressing risk-adjusted returns on only the optimistic and neutral dummy variables while allowing for an intercept. This tested whether quarterly returns from portfolios formed in optimistic and neutral periods were significantly different from those formed in pessimistic periods. These approaches followed Cooper et al. (2004) and Antoniou et al. (2013) in comparing returns across different periods of market or sentiment states. It allowed for the use of Huber-White standard errors in computing t-statistics that were robust to heteroskedasticity. As stated earlier, the use of quarterly returns data effectively eliminated the problem of serial correlation.

The above test for formation period sentiment (section 5.2.2) was repeated for holding period sentiment (5.2.3) with the results reported separately.

4.9 Limitations

Any empirical finance study needs to consider various limitations, assumptions and approximations.

4.9.1 Asset Pricing Model

A major construct used in the study, residual momentum, relied on excess returns. To determine excess returns, an asset pricing model was required to determine expected returns based on known risk factors. No perfect asset pricing model exists as yet, thus this aspect inevitably posed a validity concern for the study.

However, the basis on which the factors incorporated into the characteristic portfolios (used to determine expected returns and, by extension, unexpected or residual returns) were chosen, was well documented with strong support in the literature. These factors included size, value and industry.

Size and value notably formed part of Fama and French's (1992) three-factor model with excess market returns as the third factor. Their three-factor model was found to explain average returns in the US markets better than the CAPM. There have been various attempts to improve on the Fama-French three factor model such as Carhart's (1997) four factor model that included a factor for momentum. Fama and French themselves proposed a five factor model that considered profitability and investment as two factors additional to the original three (2015). Foye, Mramor and Pahor (2013) proposed an alternative three factor model for emerging markets that considered accounting manipulation instead of the size factor as per the original three factor model. Asness et al. (2013) suggested a three factor model that included global value and momentum factors combined with a market index. While all of the above mentioned studies claimed improvement over the Fama-French three factor model, none have achieved the same widespread adoption as yet. The three-factor model has also been used in prominent international literature on, specifically, the determination of residual momentum (Blitz et al., 2011).

Importantly, both size and value have been found to be significant factors in explaining cross-sectional differences in returns on the JSE (Fraser & Page, 2000; Strugnell, Gilbert & Kruger, 2011; Van Rensburg & Robertson, 2003). The use of the PE ratio as proxy for value also found precedence in the work of Van Rensburg and Robertson (2003) and Gilbert et al. (2011).

Van Rensburg (1995) found the industry in which a firm operated to moderate the influence of macroeconomic variables on returns. The dichotomy between different sectors on the JSE have also been acknowledged by various authors (Basiewicz & Auret, 2010; Beelders, 2003; Muller & Ward, 2013; Van Rensburg & Robertson, 2003). Specifically, the difference between resources and non-resources counters have been highlighted by authors such as Barr, Kantor and Holdsworth (2007). To account for this, the type of industry was included as a factor in the asset pricing model with firms classified as either operating in a resources industry or a non-resources industry.

4.9.2 Investor Sentiment Proxy

The selection of a proxy for investor sentiment raised a further validity concern. The study used the CCI as the basis for an approximation of investor sentiment on the JSE. While content validity could be assumed based on the interview content, internal validity was challenged by subject selection and testing effects (Saunders & Lewis, 2012). The populations associated with each construct differed in that the CCI considered the entire adult population of the country of which only a fraction included active investors on the

JSE. Foreign based investors were also not eligible for sampling through the CCI. The macro-economic variables against which the sentiment proxy was regressed were also specific to South Africa and this again excluded foreign investors and disregarded the foreign operations of companies listed on the JSE.

Finally, as a survey based index, it could also potentially suffer from measurement inaccuracies due to the various biases in play during face-to-face interviews.

Regardless, consumer confidence has been successfully used in prominent international and local literature as a proxy for investor sentiment (Antoniou et al., 2013; Lemmon & Portniaguina, 2006; Solanki & Seetharam, 2014). Moreover, the index utilised by this study was constructed through a professional research organisation and measurement bias risks were reduced as far as possible, mitigating the threat to the measure's face validity.

The choice of macroeconomic variables used to determine the portion of the CCI relating to excess investor sentiment was done as objectively as possible and was based on literature (Lemmon & Portniaguina, 2006; Solanki & Seetharam, 2014) and availability of data in the South African market. Additional tests were conducted using the raw CCI data in order to check the influence of the choice of macroeconomic variables on the results.

The break points used for classifying the different investor sentiment periods as optimistic, neutral or pessimistic was again chosen as objectively as possible. It was derived from the ratios used by Antoniou et al. (2013). The data was also analysed using alternative break points with results reported separately.

4.9.3 Other Validity Concerns

The population definition and sampling considered only the top 160 shares on the JSE and only included stocks once they had been listed for two years. The same restrictions were placed on the selection of stocks used in the determination of the characteristic portfolios used in the asset pricing model. This posed a threat to internal validity due to subject selection (Saunders & Lewis, 2012, p. 127) as a large number of JSE-listed shares were not included. However, the methodology followed other researchers in excluding small and illiquid stocks as these factors could confound the results of the research (Basiewicz & Auret, 2009; Fama & French, 1992; Muller & Ward, 2013).

4.9.4 Transaction Costs

Transaction costs arising from quarterly portfolio rebalancing were ignored in this study based on the assumption that these transaction costs would be approximately the same across portfolios both within and across investment styles. These costs would therefore have only a negligible effect on the comparison between the different momentum styles and across different sentiment periods.

However, actual returns realised through the application of these styles will be lower than hypothesised here due to the effect of transaction costs. The optimal holding and formation periods determined in section 5.1.2 could also be significantly impacted by transaction costs.

4.9.5 Generalisability

While the study drew from local and international literature, the empirical analyses were conducted in the context of the Johannesburg Stock Exchange. Structural considerations such as size, liquidity and dominant industries may be different in this market compared to other markets and this could conceivably alter the results obtained. Inferences made directly from this study should thus be restricted to the JSE itself.

Results were obtained and tested on historical data only. Findings should be considered holistically and should not recklessly be applied to future investment strategies.

5 Results

The results that follow were presented according to the two main research questions and their associated hypotheses. The main research questions concerned the following:

- A comparison between the risk-adjusted profitability of conventional momentum and residual momentum strategies on the JSE. With no prior research on residual momentum on the JSE, the results into the investigation of the viability and efficacy of residual momentum as an investment style was presented at the outset in sections 5.1.2 and 5.1.3.
- The effect of investor sentiment on the profitability of conventional and residual momentum strategies on the JSE.

5.1 Results for Research Question 1

5.1.1 Descriptive Statistics

The dataset consisted of the largest 160 stocks on the JSE according to market capitalization at the time of portfolio formation. Data was available from early 1987. Due to the requirement of establishing betas related to the asset pricing model used, at least two years of data was required before reliable residual returns could be calculated. The first portfolios were therefore created as from 31 March 1989 and results were available up to and including 30 June 2016. This allowed for a total of 327 months or 109 quarters worth of returns data for each of the portfolios.

Stocks were ranked and sorted into five equal weighted portfolios with each portfolio generally consisting of 32 stocks. Conventional momentum portfolios were created based on the stocks' cumulative total returns during the preceding twelve months, while residual momentum portfolios were created based on the stocks' cumulative residual returns during the preceding twelve months. These quintile portfolios were rebalanced quarterly. Subsequent returns reported for all portfolios considered total monthly returns. Where cumulative performance was considered, portfolio values were initially set to 1.0 with cumulative values retained during rebalancing.

Figure 1 indicates the median residual returns of the residual momentum portfolio constituents over the formation period. ResMom1 referred to the (winner) portfolio constructed from the stocks in the top quintile with regards to the residual returns over the preceding twelve months, while ResMom5 referred to the (loser) portfolio made up of stocks in the bottom quintile.

Figure 1: Median Residual Returns during Twelve Month Formation Period of Residual Momentum Portfolio Constituents

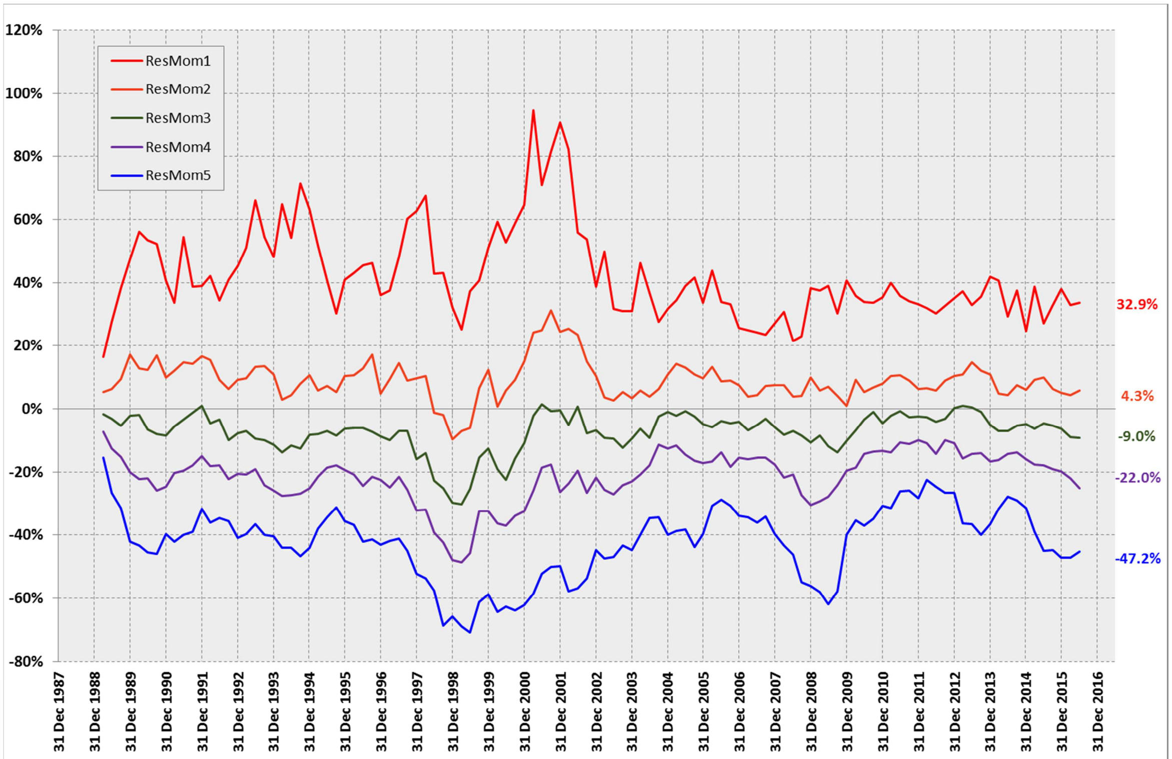


Table 3 displays various descriptive statistics regarding the returns of selected momentum portfolios over the time period studied. All five residual momentum portfolios are shown with Residual Momentum Portfolio 1 as the winner portfolio and Residual Momentum Portfolio 5 as the loser portfolio. Winner (loser) portfolio referred to the portfolio containing the stocks with the highest (lowest) cumulative residual returns over the twelve month look-back or formation period. Conventional momentum portfolios are also included, but as conventional momentum has been extensively studied in the South African market (Fraser & Page, 2000; Hoffman, 2012; Muller & Ward, 2013), only the winner (Conventional Momentum Portfolio 1) and loser (Conventional Momentum Portfolio 5) portfolios were included in the analysis.

Of particular interest towards the comparison of residual and conventional momentum were the returns obtained from zero investment strategies, long on the winner portfolio and short on the associated loser portfolio. The respective residual and conventional momentum zero-investment strategy performance results are highlighted in Table 3. The All Share Index J203 is also included in the table as a proxy for the market portfolio.

The number of samples, n, refers to the number of months' worth of returns data available for each portfolio. The mean returns and standard deviation thereof are indicated as both monthly, as well as annualised (based on monthly returns), values. Returns refer to the total returns for each variable and not excess returns. The median, skewness and kurtosis of the monthly returns data for each portfolio are also included. Finally, compound annual growth rates (CAGR) were determined from cumulative total monthly returns and are presented in the final column.

Table 3: Descriptive Statistics of Returns

		n	Mean Returns (Monthly)	Mean Returns (Annually)	Std. Deviation (Monthly)	Std. Deviation (Annually)	Median (Monthly)	Skewness (Monthly)	Kurtosis (Monthly)	CAGR
Residual Momentum	Portfolio 1	(327)	1.87%	22.43%	4.74%	16.42%	1.90%	-0.65	2.19	23.25%
	Portfolio 2	(327)	1.35%	16.26%	4.52%	15.66%	1.68%	-1.18	6.00	16.09%
	Portfolio 3	(327)	1.49%	17.83%	4.73%	16.38%	1.36%	-1.39	10.45	17.76%
	Portfolio 4	(327)	1.29%	15.46%	4.99%	17.27%	1.47%	-1.05	4.68	14.88%
	Portfolio 5	(327)	0.68%	8.22%	5.63%	19.49%	0.76%	-0.85	4.79	6.48%
	Portfolio 1 - 5	**(327)**	**1.29%**	**15.48%**	**3.58%**	**12.42%**	1.38%	**-0.19**	**0.62**	**15.75%**
Conventional Momentum	Portfolio 1	(327)	2.12%	25.45%	5.57%	19.31%	2.33%	-2.40	18.25	26.20%
	Portfolio 5	(327)	0.60%	7.18%	6.38%	22.09%	0.40%	0.05	0.50	4.88%
	Portfolio 1 - 5	**(327)**	**1.73%**	**20.78%**	**5.97%**	**20.67%**	1.88%	**-0.77**	**3.45**	**20.32%**
All Share Index	J203	(327)	1.35%	16.18%	5.29%	18.33%	1.60%	-1.07	5.77	15.47%

5.1.2 Optimal Formation and Holding Periods

Residual momentum formation and holding periods were varied independently and systematically from one to fifteen months in order to determine the returns achieved for each period. Starting with a holding period of three months, the formation period providing the highest returns was determined. This formation period was then used to determine the best associated holding period. This process was repeated until stability was reached, indicating a local optimal result. Different holding and formation periods as starting points were investigated.

The results of the investigation are presented in Table 4. The returns column refers to the maximum annualised total returns of the residual momentum winner portfolio attained when using the optimal holding and formation periods. Ultimately, a combination using a thirteen month formation period and one month holding period provided the highest returns, as can be observed from Table 4. However, returns were only marginally different across combinations using formation periods of between five and fifteen months and holding periods of one to six months. It must be noted that transaction costs were excluded in this analysis. This limitation could significantly affect the results concerning the optimal holding period.

Table 4: Formation and Holding Periods of Residual Momentum Portfolios

Formation Period		Holding Period	
Months	Returns	Months	Returns
1	12.5%	1	22.6%
2	17.7%	2	22.4%
3	19.7%	**3**	**22.2%**
4	22.8%	4	22.4%
5	23.7%	5	22.2%
6	22.2%	6	22.0%
7	22.6%	7	21.5%
8	22.2%	8	21.3%
9	22.0%	9	21.3%
10	22.7%	10	21.2%
11	23.1%	11	21.1%
12	**22.6%**	12	21.2%
13	24.0%	13	21.5%
14	23.2%	14	20.9%
15	22.3%	15	20.6%

5.1.3 Residual Momentum

Towards the question of whether residual momentum could be considered a viable investment style, the performances of its individual portfolios were assessed through a statistical comparison of these portfolios to each other.

A statistically significant difference between portfolios would indicate that the residual momentum style was a feasible style. International literature on residual momentum (Blitz et al., 2011) indicated statistically higher returns for the winner (based on twelve month historical residual returns) portfolio than for the loser portfolio. Muller and Ward's (2013) study on style-based investing on the JSE showed a trend in the returns to portfolios constructed on twelve month total return momentum. Higher ranked portfolios provided greater cumulative returns.

The test therefore concerned the following null and alternate hypotheses:

$H_{1,0}$: $R_{RMOM5} >= R_{RMOM4} >= R_{RMOM3} >= R_{RMOM2} >= R_{RMOM1}$

$H_{1,A}$: $R_{RMOM5} < R_{RMOM4} < R_{RMOM3} < R_{RMOM2} < R_{RMOM1}$

where R_{RMOM} referred to the returns of residual momentum portfolios over the time period studied with the subscript denoting the number of the portfolio. Portfolio five (one) referred to the portfolio containing the worst (best) performing stocks in terms of residual momentum during the twelve months immediately preceding portfolio formation.

Parametric tests for differences require the assumption of normally distributed data (Montgomery, 2012; Verbeek, 2008). Shapiro-Wilk tests for normality (Shapiro & Wilk, 1965) were applied to the returns data of the five quintile residual momentum portfolios. The results are summarised in Table 5 below. With the significance values below the chosen level of significance of 0.05 for all portfolios, the Shapiro-Wilk test's null hypothesis of normal distribution was rejected in all five cases in favour of the alternate hypothesis of non-normal data distributions.

Table 5: Shapiro-Wilk Tests for Normal Distributions of Residual Momentum Portfolios Returns Data

		Shapiro-Wilk		
		df	Statistic	Sig.
Residual Momentum	Portfolio 1	327	0.985	0.002
	Portfolio 2	327	0.965	0.000
	Portfolio 3	327	0.954	0.000
	Portfolio 4	327	0.971	0.000
	Portfolio 5	327	0.970	0.000

A non-parametric alternative statistical test for difference in the form of a Jonckheere-Terpstra test for ordered alternatives was therefore conducted to compare the median monthly returns of the individual residual momentum portfolios (Leton & Zuluaga, 2007). This test was preferred, based on the a priori assumption of higher expected returns for higher ranked residual momentum portfolios (Ali et al., 2015).

Further assumptions for the test required random and independent samples (McDonald, 2009; Washington et al., 2002). Autocorrelation has been found to be a common feature of stock return time series data (Akgiray, 1989; Fama, 1965), leading to a violation of the assumption of independent samples. Autocorrelation results for the five residual momentum portfolios are presented in correlograms in Appendix 1 with significant positive correlation at a one month lag found for two of the portfolios.

However, the effect of this level of within-sample autocorrelation on the comparison of mean returns across portfolios, were assumed to be minor. To test this assumption, the Jonckheere-Terpstra test was repeated using bimonthly data, which exhibited negligible autocorrelation, with results found to be qualitatively similar. Ultimately, the results presented below were achieved assuming independent monthly returns data. The results of the tests on bimonthly data are presented in Appendix 1.

This test showed that there was a statistically significant trend, at a significance level of 0.05, of higher returns associated with portfolios created based on higher residual returns, $T_{JT}(1635) = -2.964$, $p = .003$. The null hypothesis was therefore rejected and the alternate hypothesis accepted.

Kolmogorov-Smirnov tests (McDonald, 2009) were conducted to determine whether the shape of the data distributions for the individual portfolios were identical. If so, the nonparametric test could be considered a test of location and post-hoc comparisons could allow for inferences to be made on the median returns of the various portfolios (Washington et al., 2002). The shapes of the portfolios' returns distribution was dissimilar, specifically with regards to comparisons between the bottom portfolio and the other portfolios (results summarised in Appendix 1). Post-hoc testing of pairwise comparisons involving the bottom portfolio therefore only allowed for inferences to be made on significant differences between the returns data distribution of the relevant portfolios and not between their respective medians.

The post hoc multiple pair wise comparisons revealed a significant difference, at a significance level of 0.05 and based on Bonferroni-adjusted significance values, between portfolio one and portfolio five. Bonferroni adjustments were deemed necessary to counter the increased likelihood of falsely finding a significant result induced by the number of multiple comparisons conducted (Dunn, 1961). The post hoc analysis is summarised in Table 6 below.

Table 6: Pairwise Comparison Post Hoc Analysis of Residual Return Portfolios with Bonferroni-adjusted Significance Values

		Test Statistic	Standardised Test Statistic	Significance (1-sided)	Adjusted Significance (1-sided)
Residual Momentum Portfolio 5	Residual Momentum Portfolio 4	49281	[-1.732]	.042	.417
	Residual Momentum Portfolio 3	48540	[-2.038]	.021	.208
	Residual Momentum Portfolio 2	48398	[-2.097]	.018	.180
	Residual Momentum Portfolio 1	**46040**	**[-3.073]**	**.001**	**.011***
Residual Momentum Portfolio 4	Residual Momentum Portfolio 3	52755	[-0.294]	.385	1.000
	Residual Momentum Portfolio 2	52769	[-0.288]	.387	1.000
	Residual Momentum Portfolio 1	50170	[-1.364]	.086	.863
Residual Momentum Portfolio 3	Residual Momentum Portfolio 2	53484	[-0.008]	.497	1.000
	Residual Momentum Portfolio 1	50451	[-1.124]	.131	1.000
Residual Momentum Portfolio 2	Residual Momentum Portfolio 1	50749	[-1.247]	.106	1.000

*. The difference is significant at the 0.05 level.

In addition to the above tests, the cumulative total returns of each of the five quintile residual momentum portfolios were plotted on a time-series graph. This provided richer detail and allowed for visual comparison of the performance of the various residual momentum portfolios over the time period studied.

This graph is provided in Figure 2. The performance of a static investment in the All Share Index (back dated to 1989) is also displayed. The final curve presented on the graph is *ResMomZero*, referring to the returns of an ungeared zero investment strategy based on the returns of the residual momentum portfolios. The cumulative returns of the top quintile (portfolio *ResMom1*) were divided by that of the bottom quintile (portfolio *ResMom5*) across the time period. This was thus effectively the excess returns to an investor that sells the loser portfolio and buys the winner portfolio.

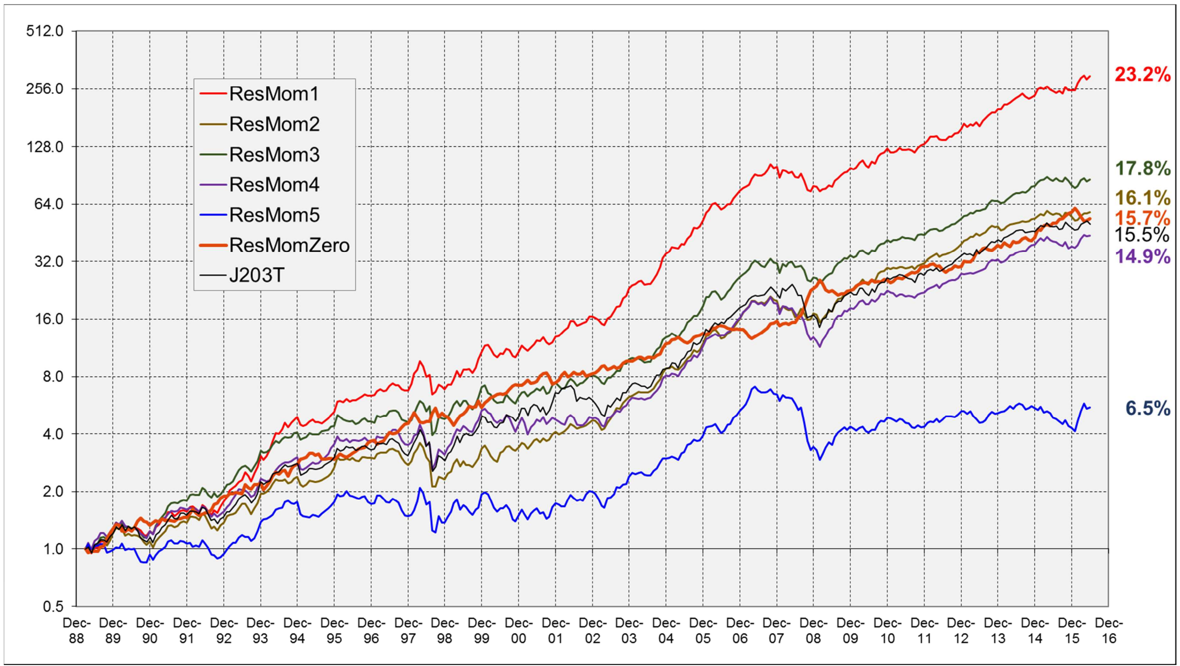
The slope of the zero investment strategy's returns could be interpreted in the following way:

- A positive slope indicated a period where the strategy was profitable and the residual momentum winner portfolio outperformed the loser portfolio.
- A flat slope indicated a neutral period
- A negative slope indicated a period where the strategy was loss-making and the residual momentum winner portfolio underperformed the loser portfolio.

The angle and length of the slopes show the extent and duration of the relative performance of the winner/loser portfolios as per the above scenarios. The curves also provide a graphic indication of the volatility inherent in the results.

The compound annual growth rates of the portfolios are displayed on the right hand side of the graph as an indication of the total performance of the portfolios over the period studied.

Figure 2: Graphical Time-Series of Residual Momentum Portfolio Returns



5.1.4 Comparison of Residual and Conventional Momentum: Cumulative Returns

Whilst common in literature, statistical analyses comparing average or median monthly returns have the shortcoming where the mean or median returns possibly do not accurately reflect the effect of outliers on the actual financial position of an investor's portfolio. As indicated by the skewness and kurtosis values in Table 3, the portfolio returns were negatively skewed with generally fat tails. A significant drawdown in a single period could erode the total value of the invested portfolio to such an extent that subsequent returns are much smaller in absolute terms. Muller and Ward (2013) also referred to the comparison of mean returns to test for differences as "methodologically weak" (p. 4) due to this effect.

The primary analysis followed was rather a graphical time-series comparison of the cumulative returns of the various portfolios as this was deemed to be more powerful in revealing persistent and significant differences across portfolios. This method also provides visual information on returns patterns during the time period studied, on the volatility of the different portfolios and on the magnitude and duration of performance differentials. Cumulative returns provided a measure of risk adjusted returns as the asymmetric effect of gains and losses on total performance was taken into account.

The first hypothesis used in the comparison of the performance of residual momentum and conventional momentum was based on the strategies' cumulative returns over the time period under review. Note that the graphical time-series approach followed below does not allow for formal hypothesis testing, and that the hypothesis was provided as a guide only.

$H_{2,0}$: $\boldsymbol{R_{CMOM} - R_{RMOM} = 0}$

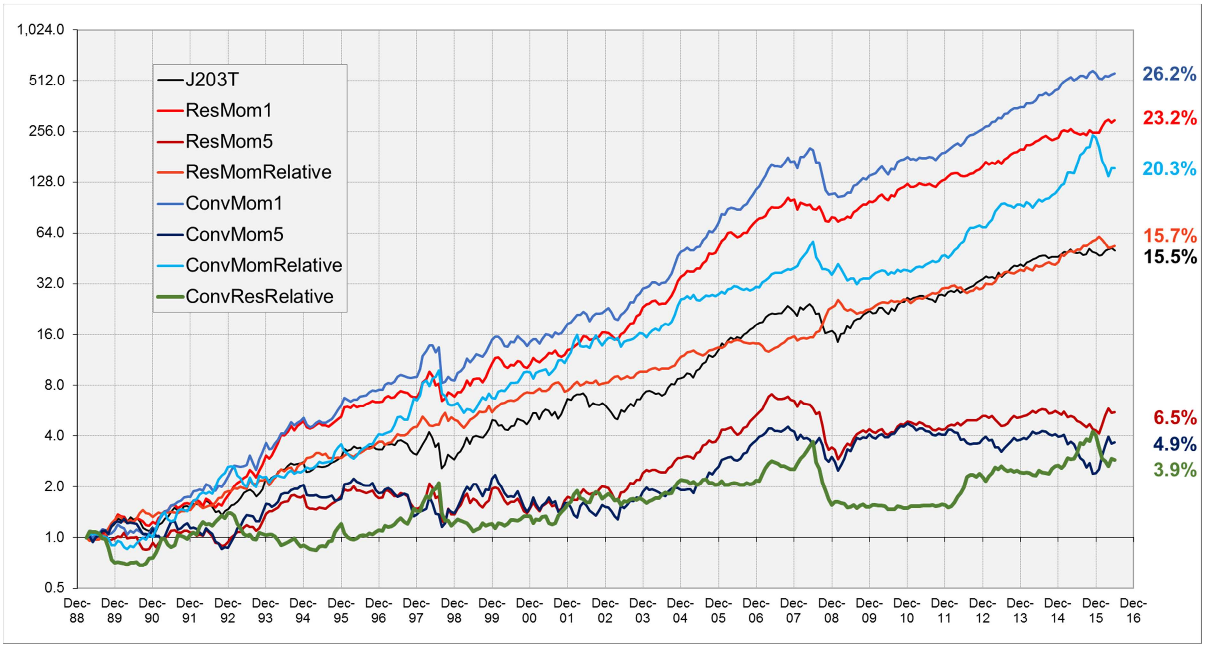
$H_{2,A}$: $\boldsymbol{R_{CMOM} - R_{RMOM} <> 0}$

The graphical time-series approach consisted of plotting the cumulative returns of the winner and loser residual momentum based portfolios as well as their conventional momentum based counterparts. Also included were the returns of zero-investment strategies for both residual and conventional momentum, named *ResMomZero* and *ConvMomZero* respectively. These returns were determined from the differences in returns between each strategy's top and bottom quintile portfolios and represented the returns to a zero-investment strategy, excluding interest on the margin account.

Finally, the performances of the residual and conventional momentum strategies were compared by plotting a relative returns curve. Named *ConvResRelative* in Figure 3, it was determined by dividing the cumulative returns of conventional momentum's zero investment strategy by that of residual momentum. This curve should be interpreted such that a positive (negative) slope of the curve provides an indication of relative outperformance (underperformance) of conventional momentum over residual momentum, while a flat portion of the curve indicates similar performance from the two strategies. The angle and length of slopes in the curve provide indications of the severity and duration of these relative performance differences.

Compound annual growth rates are indicated on the right hand side of the graph, providing an indication of relative performance over the total period under review.

Figure 3: Graphical Time-series Comparison of Residual and Conventional Momentum



5.1.5 Comparison of Residual and Conventional Momentum: Tests for Differences

Statistical tests for differences were conducted as supplementary tests to the cumulative returns considered above. Three separate statistical tests for differences were conducted to compare the performance of residual and conventional momentum. The respective winner, loser and zero-investment portfolios were compared. Each tests considered a two-tailed hypothesis, at a 0.05 significance value, as stipulated below.

- The monthly total returns of the momentum styles' respective winner portfolios were compared.

$$H_{3,0}: \quad \tilde{R}_{RMOM1} - \tilde{R}_{CMOM1} = 0$$

$$H_{3,A}: \quad \tilde{R}_{RMOM1} - \tilde{R}_{CMOM1} <> 0$$

- The monthly total returns of the styles' loser portfolios were compared.

$$H_{4,0}: \quad \tilde{R}_{RMOM5} - \tilde{R}_{CMOM5} = 0$$

$$H_{4,A}: \quad \tilde{R}_{RMOM5} - \tilde{R}_{CMOM5} <> 0$$

- The monthly performances of zero-investment strategies based on the two momentum styles were compared.

$H_{5,0}$: $\tilde{R}_{RMOM1\text{-}5} - \tilde{R}_{CMOM1\text{-}5} = 0$

$H_{5,A}$: $\tilde{R}_{RMOM1\text{-}5} - \tilde{R}_{CMOM1\text{-}5} <> 0$

Shapiro-Wilk tests were used to determine whether the above portfolios satisfied the assumption of normal distribution necessary to allow the use of parametric testing. For each of the six portfolios (Table 7), the Shapiro-Wilk test's null hypothesis of normality was rejected at a significance level of 0.05 and the alternative hypothesis of non-normal data distribution was accepted. This precluded the use of parametric tests for differences on the untransformed data sets.

Table 7: Shapiro-Wilk Test of Residual and Conventional Momentum Portfolios Returns Data

		Shapiro-Wilk		
		df	**Statistic**	**Sig.**
Residual Momentum	Portfolio 1	327	0.985	0.002
	Portfolio 5	327	0.970	0.000
	Portfolio 1 - 5	327	0.970	0.000
Conventional Momentum	Portfolio 1	327	0.922	0.000
	Portfolio 5	327	0.990	0.024
	Portfolio 1 - 5	327	0.974	0.000

A nonparametric alternative, namely the Mann-Whitney U test (McDonald, 2009), was applied. The requisite assumptions (McDonald, 2009; Washington et al., 2002) of a continuous or ordinal dependent variable and two categorical, independent groups for the independent variable were all met by the data. Some autocorrelation was evident in the data, violating the assumption of independent observations (autocorrelation test results in Appendix 1). However, the effect was expected to be minor and the tests were conducted with the assumption of independent samples in place. Additional analyses using bimonthly returns data, which was sufficient to eliminate any indication of autocorrelation, were conducted with qualitatively similar results recorded (Appendix 1, Table 22).

Kolmogorov-Smirnov tests were applied to test if the shapes of the data distributions were similar in order to determine whether the Mann-Whitney results could be applied as a comparison of median returns or only of mean ranks. It was found that equal distribution shapes could be assumed for the winner portfolios and well as for the loser portfolios, but not for the zero-investment strategies' returns. The Kolmogorov-Smirnov test results are detailed in Table 21 in Appendix 1.

Ultimately, no significant differences were found in any of the comparisons done. At an alpha level of 0.05 and with two-tailed p-values, the difference between the medians of the residual and conventional momentum's winner portfolios was not significant, U = 51033, p = .314. A similar test showed that the difference between the median returns of the two momentum styles' bottom portfolios was also non-significant, U = 51851, p = .504. In both these cases, the results meant failure to reject the null hypothesis of equal median returns.

The differences between the returns distributions of the respective zero-investment strategies were also found to not be statistically significant at a significance level of 0.05, U = 50098, p = .162. The results failed to reject the test's null hypothesis of equal returns distributions.

5.1.6 Comparison of Residual and Conventional Momentum: Sharpe Ratios

A comparison, using standard risk-adjusted performance measures, of residual momentum and conventional momentum was conducted. Zero-investment strategies, based on residual momentum and conventional momentum respectively, were used as the primary measures to compare the performance of the momentum styles using their respective unconditional ex-post Sharpe ratios.

$H_{6,0}$: $SR_{CMOM1\text{-}5} - SR_{RMOM1\text{-}5} = 0$

$H_{6,A}$: $SR_{CMOM1\text{-}5} - SR_{RMOM1\text{-}5} <> 0$

The results are summarised in Table 8. Annualised values of mean returns, standard deviations and Sharpe ratios were used.

Table 8: Sharpe Ratio Comparison of Momentum Styles (Zero-investment)

	Residual Momentum Portfolios 1-5	Conventional Momentum Portfolios 1-5
Mean Returns	15.48%	20.78%
Standard Deviation	12.42%	20.67%
Sharpe Ratio	1.25	1.01

In addition, the winner residual momentum and conventional momentum portfolios as well as the market, proxied by the All Share Index, were compared by means of their Sharpe ratios. The Sharpe ratio was based on a differential return (Sharpe, 1994) or a zero-investment strategy. It was assumed that money was borrowed at the risk-free rate in order to invest in the respective portfolios resulting in the differential return used in the Sharpe ratio calculations consisting of the portfolio's returns minus the returns on a risk-free investment. The risk-free rate was determined from the South African Reserve Bank's 91-day Treasury bill returns.

Table 9: Sharpe Ratio Comparisons of Momentum Styles (Long only)

	Residual Momentum Portfolio 1	Conventional Momentum Portfolio 1	Market (All Share Index) J203
Mean Excess Returns	11.94%	14.96%	5.69%
Standard Deviation	16.58%	19.47%	18.49%
Sharpe Ratio	0.72	0.77	0.31

5.1.7 Comparison of Residual and Conventional Momentum: Relative Risk Measures

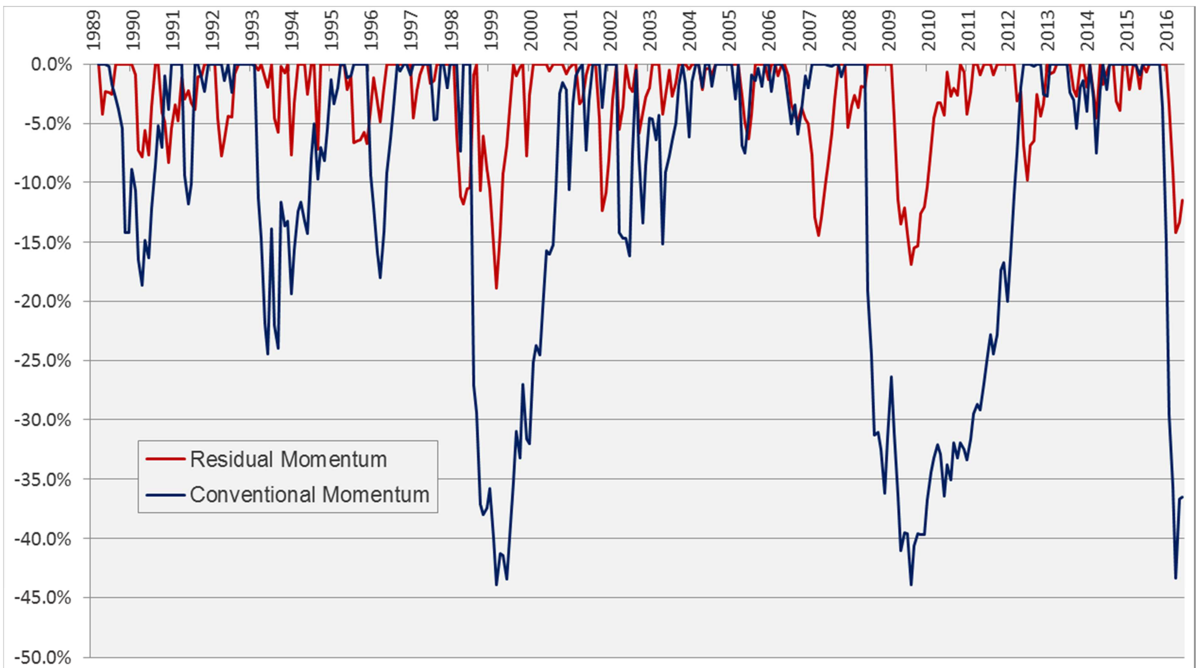
As a further relative risk indication, the best and worst months for the residual and conventional momentum styles during the review period are provided in Table 10. This gives some indication as to the maximum downside risk and upside opportunities of these strategies based on historical performance. The returns in Table 10 were based on the returns of a zero-investment strategy.

Table 10: Best and Worst Monthly Returns Experienced

	Residual Momentum		Conventional Momentum	
	Month	Returns	Month	Returns
Worst Monthly Returns	October 1998	-10.70%	August 1998	-27.08%
	November 2001	-8.08%	July 2008	-19.11%
	December 1999	-7.72%	February 2016	-17.14%
Best Monthy Returns	October 2008	12.1%	February 1998	18.93%
	July 1993	12.1%	November 2015	17.50%
	January 2015	10.7%	February 2002	17.26%

Figure 4 illustrates the drawdown experienced by the zero-investment portfolios of the two momentum strategies employed. The drawdown at time *t* was defined as the ratio between the cumulative returns at time *t* to the maximum cumulative returns up to time *t*, minus 1. This was similar to the drawdown analysis conducted by Blitz et al. (2011). The graph provides a visual indication of the magnitude, frequency and duration of drawdowns experienced by the momentum strategies.

Figure 4: Drawdown Graph of Residual and Conventional Momentum



5.2 Results for Research Question 2

5.2.1 Descriptive Statistics and Sentiment Index

The FNB BER CCI (First National Bank, Bureau of Economic Research, Consumer Confidence Index) over the period under review consisted of quarterly data in a net balance format. The index provided an absolute measure of consumer confidence at a point in time, with the value provided assumed to be indicative of the average consumer confidence during the quarter. Higher scores indicated greater positive levels of consumer confidence, while lower and negative scores indicated greater negative levels of consumer confidence.

The CCI was regressed against the following measures to determine a cleaner proxy of excess sentiment not justified by macroeconomic conditions:

- Inflation
- Employment growth
- Industrial production growth
- GDP growth
- Yield on treasury bills

The resultant equation from the ordinary least squares regression was:

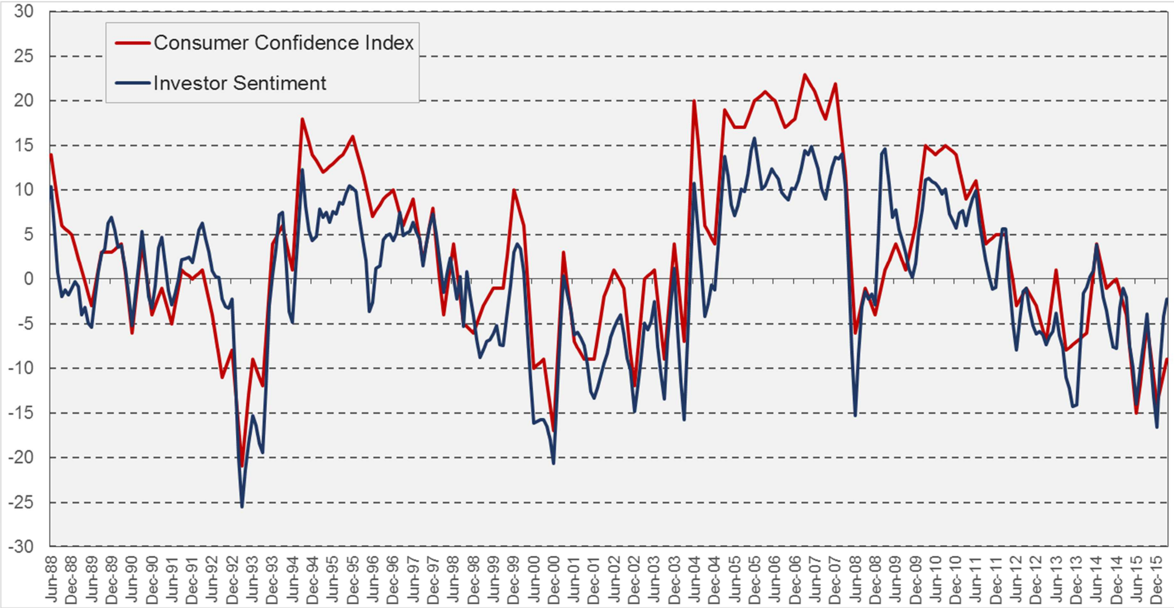
$$CCI_t = -1.196 + 17.274 \cdot GDP_t - 5.172 \cdot EG_t + 0.425 \cdot Inflation_t + 0.058 \cdot YTB_t - 0.023 \cdot IPG_t + \varepsilon_t \qquad (7)$$

where CCI_t denoted the consumer confidence index, $Inflation_t$ referred to the inflation during month t as measured through the consumer price index, EG_t referred to the monthly employment growth figure as percent change in people employed, IDP_t and GDP_t were respectively the industrial production growth and gross domestic product growth in month t and YTBt was the average quoted yield on South African treasury bills during month t.

The residual, $\mathcal{E}_t$, of the resultant measure was taken as a proxy for excess investor sentiment in the South African market, defined as sentiment that is not explained by fundamentals and macroeconomic conditions. The regression had an adjusted R^2 value of 0.189 and an F-statistic of 16.61, indicating that, whilst statistically significant, only a small portion of investor sentiment could be explained by fundamentals represented by the macroeconomic variables chosen. The significance value of each predictor was provided in Appendix 2, Table 23.

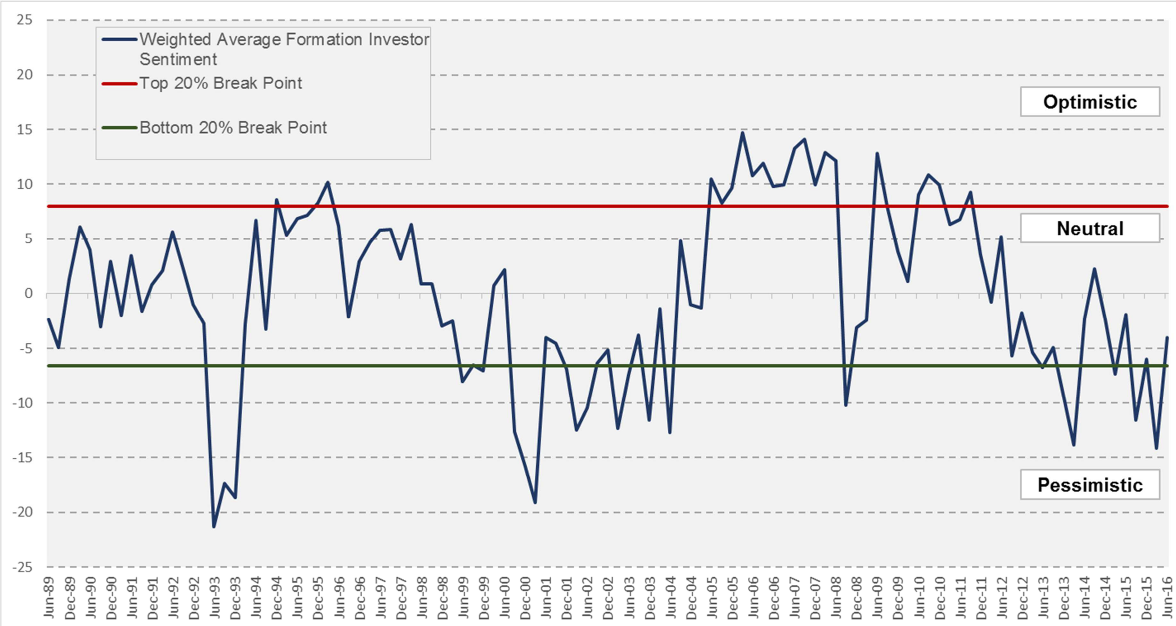
The monthly investor sentiment measure was graphed, together with the raw CCI, in Figure 5 below. The analysis primarily used the residual of the regressed CCI as per Equation 7 as the investor sentiment proxy, but a secondary analysis using only the raw CCI was conducted (results summarised in Appendix 2) to ensure that the results obtained were not due to overfitting of the model by the choice of macroeconomic variables.

Figure 5: Consumer Confidence Index and Investor Sentiment Proxy



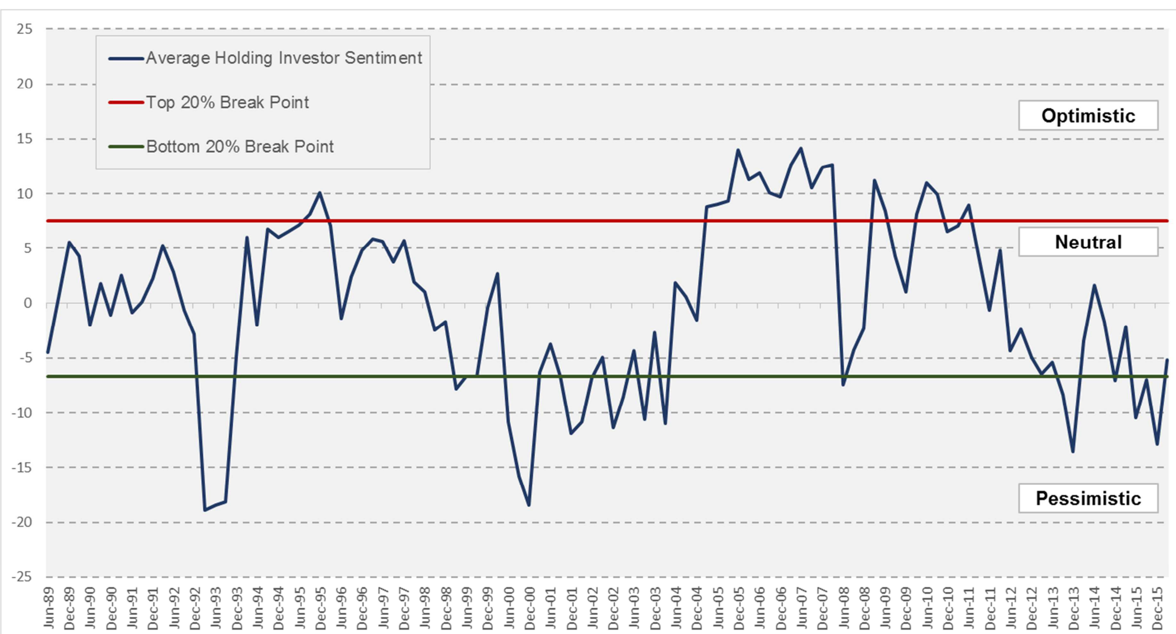
The state of investor sentiment during each quarter was defined according to the value of the investor sentiment proxy for the associated quarter, weighted towards the most recent months, similar to the approach followed by Antoniou et al. (2013). All the quarters included in the time series were ranked and quarters with the lowest (bottom 20 percent of cases) and highest (top 20 percent of cases) sentiment were defined as periods of pessimistic and optimistic sentiment respectively. The sentiment states of the remaining quarters were deemed to be neutral. Alternative break points were also investigated; namely the 15th/85th percentiles and 30th/70th percentiles. Figure 6 indicates the resultant investor sentiment states across the time-series illustrating the 20th/80th percentiles break points.

Figure 6: Classification of Investor Sentiment States based on Weighted Average Formation Sentiment



The effect of investor sentiment on momentum returns during the holding period was also investigated. The investor sentiment state of each holding period was determined from the arithmetic mean of the level of investor sentiment during the three month holding period following portfolio formation. Quarterly holding period investor sentiment across the time series is shown in Figure 7 with optimistic (top 20 percent) and pessimistic states' (bottom 20 percent) break points included.

Figure 7: Classification of Investor Sentiment States based on Average Holding Sentiment



5.2.2 Comparison of Mean Returns of Residual and Conventional Momentum Conditional on Formation Period Investor Sentiment

Quarterly momentum returns were assessed based on the different sentiment states during the formation period with sentiment states determined from the weighted average level of sentiment during the three months directly preceding portfolio formation. The null and alternate hypotheses were:

$$\mathbf{H_{7,0}}: \quad \bar{R}_{RMOM,PES\text{-}FORM} = \bar{R}_{RMOM,NTR\text{-}FORM} = \bar{R}_{RMOM,OPT\text{-}FORM}$$

$$\mathbf{H_{7,A}}: \quad \bar{R}_{RMOM,PES\text{-}FORM} <> \bar{R}_{RMOM,NTR\text{-}FORM} <> \bar{R}_{RMOM,OPT\text{-}FORM}$$

and

$$\mathbf{H_{8,0}}: \quad \bar{R}_{CMOM,PES\text{-}FORM} = \bar{R}_{CMOM,NTR\text{-}FORM} = \bar{R}_{CMOM,OPT\text{-}FORM}$$

$$\mathbf{H_{8,A}}: \quad \bar{R}_{CMOM,PES\text{-}FORM} <> \bar{R}_{CMOM,NTR\text{-}FORM} <> \bar{R}_{CMOM,OPT\text{-}FORM}$$

$\bar{R}$ referred to mean monthly returns, subscripts CMOM and RMOM referred to conventional momentum and residual momentum respectively, PES, OPT and NTR referred to pessimistic, optimistic and neutral sentiment states and FORM denoted formation period. For example, $\bar{R}_{RMOM,PES\text{-}FORM}$ indicated the mean returns to a residual momentum strategy following a pessimistic formation period.

Mean quarterly returns were determined by linear regression of the returns of the various portfolios on dummy variables for sentiment states (Antoniou et al., 2013; Cooper et al., 2004; Verbeek, 2008). An initial regression was done for each of the portfolios with a dummy variable for each state but no intercept. The slope of the dummy variable terms in the regression expression represented mean returns following each sentiment state. T-stats were calculated from the Huber-White standard errors (White, 1980) and were used to determine whether these slopes were significantly different from zero. The Huber-White standard errors were robust to heteroskedasticity (Verbeek, 2008; White, 1980).

An additional regression for each portfolio was conducted without the dummy variable for the pessimistic sentiment state but with an intercept included. The slopes of the remaining dummy variables represented the difference of mean returns following these states relative to that of pessimistic sentiment states. T-stats were again determined from the Huber-White standard errors in order to determine whether these differences were statistically significant.

A number of assumptions were to be met to allow the valid use of linear regression with only dummy independent variables in the statistical analysis (Montgomery, 2012; Osborne & Waters, 2002). These included the following:

- Normality of error distribution

  The residual of each regression was tested using the Shapiro-Wilk test for normality (Shapiro & Wilk, 1965). The results of these tests are reported in columns three to five of Table 11. This test had the null hypothesis that the data being tested were normally distributed. A significance value below 0.05 would mean that the null hypothesis is to be rejected and the alternate hypothesis of non-normal data distribution to be accepted.

- Little or no autocorrelation

  The Durbin-Watson test statistic (Verbeek, 2008) for each regression was also determined and these results are supplied in column six of Table 11. This test provides an indication of the level of autocorrelation present in the data with a test statistic of two indicating no autocorrelation. A substantial deviation from two would indicate autocorrelation in the data.

  Based on the number of regressors (two plus intercept) and sample size (109), the dL (1.634) and dU (1.715) values were the same for all regressions conducted. These values were taken into account and Table 11, columns seven and eight specifically, summarises the lower limit (L-L) and upper limit (U-L) for the Durbin-Watson test statistic outside of which the null hypotheses of no positive serial correlation and no negative serial correlation would be rejected.

  Ultimately, no autocorrelation was evident in any of the linear regressions conducted. This was likely due to the study's consideration of quarterly returns instead of shorter frequency returns data.

- Homoskedasticity

  The use of Huber-White robust errors meant that the results were not sensitive to violations of this assumption (Verbeek, 2008; White, 1980).

Table 11: Tests of Assumptions for Linear Regression on Dummy Variables

Dependent Variable		df	Shapiro-Wilk Statistic	Shapiro-Wilk Sig.	Durbin-Watson D	Durbin-Watson L-L	Durbin-Watson U-L
Residual Momentum	Portfolio 1	109	0.978	.067	1.964	1.715	2.285
	Portfolio 5	109	0.993	.888	1.990	1.715	2.285
	Portfolio 1 - 5	109	0.979	.085	2.192	1.715	2.285
Conventional Momentum	Portfolio 1	109	0.922	.000	1.878	1.715	2.285
	Portfolio 5	109	0.973	.024	2.196	1.715	2.285
	Portfolio 1 - 5	109	0.970	.013	2.073	1.715	2.285
Market	ALSI (J203)	109	0.975	.037	2.082	1.715	2.285

Important to note from Table 11 above is the failure of the Shapiro-Wilk test by the conventional momentum portfolios. The Shapiro-Wilk test's alternate hypothesis of non-normal distribution was therefore accepted for these portfolios. The results of the associated regressions were still presented in Table 12 for ease of reference, but the t-stats and significance values of the difference between returns following optimistic and pessimistic formation periods were not presented for these portfolios. The violation of the normal distribution assumption could significantly affect the results and thus precluded the drawing of statistical inferences from the results.

Table 12 shows the mean quarterly returns of the winner, loser and zero-investment (refer to columns named "Relative") portfolios of the residual momentum and the conventional momentum strategies based on the state of investor sentiment during the final quarter of the portfolio formation period. T-statistics were supplied to determine the statistical significance of the mean returns relative to zero of the zero-investment strategy for each sentiment state. The row "Optimistic-Pessimistic" provides the mean difference in quarterly returns for each portfolio following optimistic and pessimistic formation periods with the associated robust t-statistics supplied underneath. The significant values provided were all based on two-tailed hypothesis testing. The break points for the definition of sentiment states were set at the 20^{th} and 80^{th} percentiles. Alternative break points were also investigated and are shown in Table 13 and Table 14. The testing of the assumptions required for the linear regression on dummy variables using these alternative sentiment break points were summarised in Appendix 2, Table 24 and Table 25.

Table 12: Mean Quarterly Returns Conditional on Investor Sentiment during Formation Period (20th/80th Percentiles as Break Points)

		Residual Momentum Portfolios					Conventional Momentum Portfolios					Market (ALSI)		
State	n	Loser	Winner	Relative	t-stat	Sig.	Loser	Winner	Relative	t-stat	Sig.	J203	t-stat	Sig.
Mean profits following different sentiment states:														
Optimistic	(22)	**5.28**	**6.86**	1.65	[1.40]	.160	5.77	9.64	4.19	[2.10]	.036	6.48	[4.88]	.000
Neutral	(66)	1.20	**4.80**	**4.04**	[4.68]	.000	0.17	6.07	6.67	[4.74]	.000	3.18	[2.87]	.004
Pessimistic	(21)	1.87	**7.47**	**6.00**	[4.41]	.001	3.52	4.93	3.15	[0.85]	.396	4.39	[1.71]	.088
Statistical comparison of mean profits following different sentiment states:														
Optimistic-Pessimistic		3.41	-0.62	**-4.35**										
t-stat		[1.01]	[-0.21]	[-2.42]										
Sig.		.311	.837	.016										

Table 13: Mean Quarterly Returns Conditional on Investor Sentiment during Formation Period (30th/70th Percentiles as Break Points)

		Residual Momentum Portfolios					Conventional Momentum Portfolios					Market (ALSI)		
State	n	Loser	Winner	Relative	t-stat	Sig.	Loser	Winner	Relative	t-stat	Sig.	J203	t-stat	Sig.
Mean profits following different sentiment states:														
Optimistic	(33)	**4.36**	**6.70**	**2.43**	[2.57]	.010	4.23	8.90	4.95	[2.89]	.004	**6.07**	[4.81]	.000
Neutral	(44)	0.15	**4.35**	**4.66**	[4.21]	.000	-0.49	5.26	6.49	[3.72]	.000	2.12	[1.77]	.076
Pessimistic	(32)	2.63	**6.63**	**4.50**	[3.74]	.000	2.95	5.97	4.67	[1.70]	.089	**4.72**	[2.25]	.024
Statistical comparison of mean profits following different sentiment states:														
Optimistic-Pessimistic		1.73	0.07	-2.07								1.35		
t-stat		[0.63]	[0.03]	[-1.35]								[0.55]		
Sig.		.530	.975	.177								.580		

Table 14: Mean Quarterly Returns Conditional on Investor Sentiment during Formation Period (15th/85th Percentiles as Break Points)

		Residual Momentum Portfolios					Conventional Momentum Portfolios					Market (ALSI)		
State	n	Loser	Winner	Relative	t-stat	Sig.	Loser	Winner	Relative	t-stat	Sig.	J203	t-stat	Sig.
Mean profits following different sentiment states:														
Optimistic	(17)	**5.25**	**6.31**	1.18	[0.97]	.334	6.39	9.31	3.36	[1.55]	.120	6.51	[5.34]	.000
Neutral	(76)	1.70	**5.42**	**4.13**	[5.15]	.000	0.61	6.76	6.90	[5.24]	.000	3.81	[3.61]	.000
Pessimistic	(16)	1.01	**6.60**	**5.95**	[3.92]	.000	3.56	2.77	1.06	[0.24]	.809	2.78	[0.92]	.356
Statistical comparison of mean profits following different sentiment states:														
Optimistic-Pessimistic		4.24	-0.29	**-4.77**										
t-stat		[1.13]	[-0.09]	[-2.45]										
Sig.		.257	.932	.014										

With reference to Table 12, the null hypothesis of equal returns across sentiment states was rejected for the residual momentum style at the 0.05 significance level and the alternate hypothesis was accepted. A significant sentiment effect on a residual momentum style on the JSE was therefore apparent. The effect on conventional momentum was inconclusive. However, trends in the data did seem to indicate higher returns for conventional momentum following neutral and optimistic periods than following pessimistic periods.

The returns provided by a strategy using conventional momentum for quarters following optimistic and neutral sentiment periods and using residual momentum following pessimistic formation periods were also investigated. Table 15 summarises the CAGR, mean annual returns, annualised volatility and Sharpe ratio of such a sentiment-based, combined momentum strategy over the course of the time series studied. Sentiment states were defined using the 20^{th} and 80^{th} percentile break points. Equivalent variables for separate residual and conventional momentum strategies are also provided (repeated from Table 8) for ease of reference.

Table 15: Returns to a Momentum Style Combined Based on Sentiment

	Residual Momentum Portfolio 1-5	Conventional Momentum Portfolio 1-5	Combined Momentum Conditional on Sentiment Portfolio 1-5
CAGR	15.75%	20.32%	24.11%
Mean Excess Returns	15.48%	20.78%	23.39%
Standard Deviation	12.42%	20.67%	17.86%
Sharpe Ratio	1.25	1.01	1.31

5.2.3 Comparison of Mean Returns of Residual and Conventional Momentum Conditional on Holding Period Investor Sentiment

Quarterly momentum returns were assessed based on the different sentiment states during the holding period where sentiment states were determined from the simple arithmetic average level of sentiment during the three month holding period following rebalancing. The null and alternate hypotheses were:

$$H_{9,0}: \quad \bar{R}_{RMOM,PES\text{-}HOLD} = \bar{R}_{RMOM,NTR\text{-}HOLD} = \bar{R}_{RMOM,OPT\text{-}HOLD}$$

$$H_{9,A}: \quad \bar{R}_{RMOM,PES\text{-}HOLD} <> \bar{R}_{RMOM,NTR\text{-}HOLD} <> \bar{R}_{RMOM,OPT\text{-}HOLD}$$

and

$$H_{10,0}: \quad \bar{R}_{CMOM,PES\text{-}HOLD} = \bar{R}_{CMOM,NTR\text{-}HOLD} = \bar{R}_{CMOM,OPT\text{-}HOLD}$$

$$H_{10,A}: \quad \bar{R}_{CMOM,PES\text{-}HOLD} <> \bar{R}_{CMOM,NTR\text{-}HOLD} <> \bar{R}_{CMOM,OPT\text{-}HOLD}$$

A similar approach to section 5.2.2 was followed. Quarterly returns data for each portfolio was initially regressed, without an intercept, on dummy variables representing different holding period sentiment states. This was followed by a regression, with an intercept, on only the optimistic and neutral state dummy variables. The slopes indicated mean returns of the portfolios during the different sentiment states and the mean differences in returns during the optimistic and neutral states compared to the pessimistic state. Huber-White robust t-statistics for the difference in returns between the winner and loser portfolios for each sentiment state and between each portfolio's returns during optimistic and pessimistic states were determined.

Similar assumptions to section 5.2.2 were required. The tests for these assumptions are provided in Appendix 2.

Table 16 shows the contemporaneous effect of investor sentiment as measured by the adjusted CCI on the quarterly returns of the winner, loser and zero-investment portfolios of residual and conventional momentum. A period was defined as optimistic (pessimistic) if its investor sentiment levels ranked it in the top 20 percent (bottom 20 percent) of periods during the time period under review. Table 17 and Table 18 show the results of using the top and bottom 30 percent and top and bottom 15 percent respectively to determine the state of investor sentiment during the holding period.

Table 16: Mean Quarterly Returns Conditional on Investor Sentiment during Holding Period (20th/80th Percentiles as Break Points)

		Residual Momentum Portfolios					Conventional Momentum Portfolios					Market (ALSI)		
State	n	Loser	Winner	Relative	t-stat	Sig.	Loser	Winner	Relative	t-stat	Sig.	J203	t-stat	Sig.
Mean profits during different sentiment states:														
Optimistic	(22)	3.48	**5.80**	**2.45**	[2.35]	.019	2.43	**8.13**	**5.72**	[4.06]	.000	**5.11**	[3.44]	.001
Neutral	(65)	1.90	**6.36**	**4.88**	[5.31]	.000	2.18	**6.37**	**5.13**	[2.98]	.003	**3.57**	[2.96]	.003
Pessimistic	(21)	1.43	**3.89**	**2.90**	[2.36]	.018	0.58	**5.74**	**6.69**	[2.44]	.015	**4.75**	[2.23]	.026
Statistical comparison of mean profits during different sentiment states:														
Optimistic-Pessimistic		2.05	1.91	-0.46								0.37		
t-stat		[0.66]	[0.80]	[-0.28]								[0.14]		
Sig.		.507	.426	.777								.888		

Table 17: Mean Quarterly Returns Conditional on Investor Sentiment during Holding Period (30th/70th Percentiles as Break Points)

		Residual Momentum Portfolios					Conventional Momentum Portfolios					Market (ALSI)		
State	n	Loser	Winner	Relative	t-stat	Sig.	Loser	Winner	Relative	t-stat	Sig.	J203	t-stat	Sig.
Mean profits during different sentiment states:														
Optimistic	(33)	**3.31**	6.24	**3.14**	[2.87]	.029	3.28	7.13	4.29	[2.74]	.006	**4.86**	[4.11]	.000
Neutral	(43)	0.95	5.62	**5.13**	[4.59]	.000	0.35	6.29	6.51	[3.16]	.002	2.99	[1.90]	.058
Pessimistic	(32)	2.49	5.47	3.37	[3.14]	.078	2.63	6.48	5.57	[2.27]	.023	**4.85**	[2.81]	.005
Statistical comparison of mean profits during different sentiment states:														
Optimistic-Pessimistic		0.82		-0.23			0.65					0.10		
t-stat		[0.32]		[-0.15]			[0.19]					[0.05]		
Sig.		.747		.879			.846					.996		

Table 18: Mean Quarterly Returns Conditional on Investor Sentiment during Holding Period (15th/85th Percentiles as Break Points)

		Residual Momentum Portfolios					Conventional Momentum Portfolios					Market (ALSI)		
State	n	Loser	Winner	Relative	t-stat	Sig.	Loser	Winner	Relative	t-stat	Sig.	J203	t-stat	Sig.
Mean profits during different sentiment states:														
Optimistic	(17)	**5.25**	7.10	**2.42**	[2.18]	.029	3.54	9.75	6.17	[4.06]	.000	5.97	[3.54]	.000
Neutral	(75)	1.66	5.63	**4.63**	[5.62]	.000	1.36	6.15	5.78	[2.98]	.000	3.43	[3.20]	.001
Pessimistic	(16)	1.01	5.00	2.73	[1.76]	.078	2.85	5.39	3.83	[2.44]	.194	5.33	[1.99]	.047
Statistical comparison of mean profits during different sentiment states:														
Optimistic-Pessimistic		1.92		-0.31										
t-stat		[0.54]		[-0.16]										
Sig.		.592		.869										

No significant differences were found between the returns of either momentum style during the different sentiment states, thereby failing to reject, at the 0.05 level of significance, the null hypotheses of equal returns across sentiment states.

6 Discussion of Results

The results provided in Chapter 5 are discussed below. Significant excess returns for both residual and conventional momentum strategies were found in the South African market, recording yet another instance of market behaviour anomalous to the Efficient Market Hypothesis of Fama (1970). In addition, investor sentiment as measured by a consumer confidence index, appeared to have had a significant effect on the residual momentum style. This indicated a violation of even the weak form of market efficiency (Fama, 1970) with stock prices apparently affected by behavioural factors.

6.1 Discussion Concerning Research Question 1

Research Question One considered the viability of residual momentum as an investment style on the JSE and evaluated the returns when using this style against using a conventional momentum style.

Firstly, residual momentum as an investment style was investigated and was found to be a feasible investment style. Concurrently, the optimal holding and formation periods for residual momentum on the JSE were also determined.

Thereafter, the risk adjusted returns of residual momentum and conventional momentum styles were compared using a number of alternative methods. The results indicated lower returns, but also reduced volatility, for residual momentum. While conventional momentum achieved greater cumulative returns, it experienced episodes of large drawdowns, highlighting the risk associated with this strategy. Ultimately, residual momentum provided greater risk-adjusted returns than conventional momentum over the time period studied.

6.1.1 Residual Momentum as an Investment Style

Momentum in financial markets refers to trend continuation in stock prices (Barroso & Santa-Clara, 2015; Chui et al., 2010; Jegadeesh & Titman, 1993). For residual momentum to be considered a viable style, a portfolio consisting of stocks constructed based on positive recent residual returns must show persistent outperformance over an associated portfolio of recent poor performers.

The results showed that there was a statistically significant trend in the returns of the five residual momentum portfolios. The loser portfolio containing shares with the lowest residual returns during the formation period had the lowest returns during the subsequent three month holding period. Correspondingly, the winner portfolio, equal weighted and containing shares with the highest residual returns during the twelve month formation period, showed the highest returns during the holding period.

These results confirmed residual momentum as a viable investment style on the JSE. This conclusion was similar to findings from international markets which indicated significant returns to investment styles similar to the residual momentum studied here (Blitz et al., 2011; Gutierrez & Pirinsky, 2007; Hühn & Scholz, 2016).

Further analysis through post hoc non-parametric tests for difference revealed the statistically significant differences to lie mainly between the two extreme portfolios. The graphical time-series plot also indicated that the loser portfolio consistently performed the worse and the winner portfolio consistently performed the best. However, the central three portfolios showed moderate performance, with no clear or consistent differences between these portfolios.

These findings were supportive of the notion that residual momentum is primarily linked to the market's under-reaction to firm-specific news (Blitz et al., 2011; Gutierrez & Pirinsky, 2007). Residual returns were assumed to be based on idiosyncratic factors and thus related to firm specific events. Gutierrez and Pirinsky (2007) found that the under-reaction phenomenon extended to firm-specific information encapsulated in returns data. From this, it can be inferred that the market would only noticeably react to firm-specific news that is sufficiently out of the ordinary. The firm specific news of the firms in the central portfolios were not noteworthy enough to overcome the noise in the market and there were no discernible differences in the returns of these portfolios.

The indifferent performance of the central three portfolios did not detract from the practical applicability of the residual momentum style. A zero-investment strategy would borrow and sell shares in the loser portfolio and buy shares in the winner portfolio. The relative performance of portfolios one and five were therefore of interest.

A residual momentum style based, zero-investment strategy would have seen a compound annual growth rate of 15.7 percent over the past 27 years. While this was similar to market returns (considering only the top 160 stocks) of 15.5 percent, it must be noted that the zero-investment strategy allows for gearing to increase returns.

The relative returns plot in Figure 2 showed a consistent upward trend, indicating that the winner portfolio consistently outperformed the loser portfolio. The periods where the loser portfolio matched or exceeded the returns of the winner portfolio were relatively minor and of short duration. These occurred in late 1998 (-18.9% total loss), middle 2009 (-16.9%)

and early-middle 2007 (-14.4%). The low levels of volatility in relative returns can be visually observed from the same time-series graph.

Finally, the effectiveness of the market neutral approach to portfolio formation can also be observed as the returns to a relative residual momentum strategy did not appear to vary with market returns. This provided some validation to the methodology followed when determining residual returns.

6.1.1.1 Optimal Holding and Formation Periods of Residual Momentum

The optimal holding and formation periods for residual momentum were also determined. The style was found to be rather insensitive to the formation and holding period employed. Formation periods of anywhere between five and fifteen months provided similar returns. Returns were also similar for holding periods between one and six months after which a gradual but steady decline was evident. It must be noted that these results were obtained without considering transaction costs. Transaction costs would likely have modified the holding period results.

This supported findings in international markets (Blitz et al., 2011; Gutierrez & Pirinsky, 2007) that residual momentum returns show little tendency for mean reversion. The average returns of the winner portfolio decreased only slightly as the holding period was increased. This was again related to market under-reaction to firm-specific news (Blitz et al., 2011), which was possibly due to conservatism (Barberis et al., 1998), institutional investor behaviour (Gutierrez & Pirinsky, 2007), the self-attribution bias (Daniel et al., 1998) or, more generally, the gradual rate of news diffusion across the market (Hong & Stein, 1999).

The short-term reversals noted by Jegadeesh (1990) and Lehmann (1990) were not evident in the data. The maximum annualised returns to the winner portfolio during the first month of the holding period was 22.6 percent on average, slightly higher even than the maximum three month annualised returns of 22.2 percent. Short-term reversals have been associated with market microstructure effects and the bid-ask bounce effect, which is greater in small and illiquid stocks (Jegadeesh & Titman, 1995; Moskowitz & Grinblatt, 1999; Novy-Marx, 2012). While other authors in related studies on conventional momentum also failed to find evidence of short-term returns reversal (Moskowitz & Grinblatt, 1999), the lack of return reversal in this study could most likely be ascribed to the portfolio formation method that ensured less exposure to small and illiquid stocks. This was achieved by firstly considering only the largest 160 stocks for inclusion in the study and secondly, preventing an abnormal concentration of small stocks in any single portfolio by using only residual returns during portfolio formation.

Ultimately, a formation period of twelve months, including the most recent month, and a holding period of three months were selected for the study. This allowed direct comparison to conventional momentum which has often been studied with similar formation and holding periods (Blitz et al., 2011; Jegadeesh & Titman, 1993; Muller & Ward, 2013). It also limited the required rate of portfolio rebalancing to four times per annum. As rebalancing incurs transaction costs, a low trading frequency held practical advantages.

6.1.2 Comparison of Residual and Conventional Momentum

Conventional momentum was found to provide greater total returns than residual momentum, but with higher associated risk. Residual momentum provided less cumulative returns over the time period studied, but did so with much lower downside risk, resulting in greater risk-adjusted returns when compared to conventional momentum using the unconditional Sharpe ratio.

6.1.2.1 Time-series Analysis of Cumulative Returns

With reference to Figure 3, residual momentum had underperformed conventional momentum over the total time period under review. The inferior performance came from both the winner and loser portfolios as the conventional momentum winner portfolio outperformed residual momentum's winner portfolio while at the same time, in the shorted loser portfolios, conventional momentum's portfolio generated lower returns than that of residual momentum.

However, the outperformance by conventional momentum was not consistent over the time period and the results were therefore dependent on the chosen start date.

The two styles performed relatively similarly until about late 1997, when conventional momentum started to perform extraordinarily well. However, this style suffered significant losses in mid-1998 when the market recovered suddenly after a substantial bear market. Residual momentum remained robust during this time, only suffering a small loss a few months later. The large drawdown suffered by conventional momentum put the two styles back on an almost equal footing.

Conventional momentum showed a small, but steady performance differential over residual momentum for most of the first decade of the 21st century. This differential increased suddenly in early 2008, but again the gap was closed when conventional momentum suffered significant losses. This time the losses were coincidental with a bear market and were due to losses in the long leg of the investment. Losses continued during the subsequent recovery due to gains in the short leg. Residual momentum appeared much more resistant to market movement over the same period, with strong gains during the market downturn and only minor losses when the market recovered.

The styles performed similarly for the next three years after which conventional momentum again provided greater returns until early 2016 when another momentum crash was experienced. Residual momentum also suffered some losses due to strong gains in the short leg of the investment, but these were again not as severe as that suffered by conventional momentum.

Figure 3 and the description above showed clearly the vulnerability of conventional momentum to so-called crashes (Daniel & Moskowitz, 2013). This was explained due to conventional momentum's time-varying exposure to common risk factors (Blitz et al., 2011; Grundy & Martin, 2001). If the market experiences strong positive (negative) movement over a period of time, the winner and loser portfolios tend to become loaded with stocks with high and low (low and high) betas respectively. When the market experiences a sudden reversal of fortunes, the winner portfolio loses when the market loses (and the loser portfolio gains when the market gains) without a corresponding response in the opposite portfolio. Both situations lead to losses in the conventional momentum zero-investment portfolio. It could be observed from Figure 3 that extreme periods in conventional momentum returns were closely aligned with significant market volatility.

At the same time, residual momentum displayed a much smoother cumulative return line, indicating robustness to systemic risk factors. Accommodating for factor-related returns in the construction of residual momentum portfolios appeared to effectively limit common exposure to these factors in any single portfolio. Systemic risks therefore affected both the long and short legs nearly equally, making the strategy almost market neutral. These results were similar to that observed in international studies (Blitz et al., 2011; Gutierrez & Pirinsky, 2007).

6.1.2.2 Statistical Comparison of Monthly Returns Data

The comparison between the monthly returns of residual and conventional momentum styles failed to reject the null hypotheses of equal returns. No statistically significant differences were found between the median monthly returns of the styles' respective winner portfolios and loser portfolios, nor were significant differences found between the returns distributions of the relative portfolios.

From Figure 3, the similarities in the performance of the two momentum styles can be observed with the main differences in total returns ascribed to short periods of volatile movement, especially in the conventional momentum style. These differences were unlikely to be observed in the comparison of median monthly returns, explaining the failure of the statistical tests for differences in group medians or distributions to reject the null hypothesis of equality. This also supported Muller and Ward's (2013) assertion that the comparison of mean or median portfolio returns applied in this manner is methodologically weak.

Further considerations regarding the shape of the monthly returns distributions revealed that residual momentum had a lower kurtosis of 0.62 compared to conventional momentum's 3.45. Residual momentum returns were also less negatively skewed, -0.19 versus -0.77 (refer to Table 3). These results implied that residual momentum had thinner tails, especially on the negative side, than conventional momentum. This in turn equated to a reduced risk of significant negative returns or crashes.

6.1.2.3 Analysis of Risk-adjusted Performances using the Sharpe Ratio

Using the Sharpe ratio as the measure for risk-adjusted performance, residual momentum proved to be superior to conventional momentum. Despite residual momentum's lower average annual returns (15.48% versus 20.78%), its much lower annualised standard deviation (12.42% versus 20.67%) meant that its Sharpe ratio was significantly higher than that of conventional momentum (1.25 versus 1.01).

Residual momentum's improved risk-adjusted performance could again be ascribed to this style's lower exposure to system risk factors due to the principle behind the construction of its portfolios. Returns related to size, value and industry were ignored when determining idiosyncratic stock momentum and deciding on whether the stock will be included in a portfolio. Blitz et al. (2011) also found, in major American markets, residual momentum to have a much higher Sharpe ratio than conventional momentum due to its lower volatility. Similar results were found for alpha momentum over conventional momentum by Hühn and Scholz (2016) in both American as well as European markets.

Residual momentum's fundamental driver of under-reaction to firm-specific news due to various possible behavioural factors could also contribute to the strategy's lower volatility. The proposed factors or models behind the under-reaction phenomenon such as conservatism (Barberis et al., 1998), slow news diffusion (Hong & Stein, 1999) and the behaviour of institutional investors under the effect of agency theory-related influences (Gutierrez & Pirinsky, 2007) were all connected with slower reactions to potential idiosyncratic mispricing, which could contribute to lower volatility. If this was the case, low volatility would be evident in the individual short and long legs of the residual momentum portfolio.

The respective Sharpe ratios of the winner portfolios of both momentum styles as well as the All Share Index were determined. As per Sharpe (1994), the average annualised excess returns above the risk-free rate was used. The Sharpe ratio of the conventional momentum strategy's winner portfolio was somewhat higher than that of residual momentum, and both momentum strategies' were more than double that of the market. Practically, an investor considering a long-only investment would thus be almost equally served by either residual or conventional momentum, with his or her risk tolerance the deciding factor. Academically, the under-reaction behind residual momentum led to lower volatility, but also lower returns and can thus not solely explain the higher risk-adjusted returns of the zero investment strategy. The improvement is more likely due to the portfolio selection method employed for residual momentum preventing an undue concentration of stocks with similar systematic risk factor loadings in either the long or short portfolio. A zero-investment, residual momentum based strategy is therefore hedged to a certain extent against systematic risk factors.

Ultimately, conventional momentum provided the greater total returns over the period under review, but it exhibited greater volatility and experienced much worse drawdowns over the period as can be observed in Table 10 and Figure 4. Residual momentum provided better risk-adjusted returns when measured according to the ubiquitous Sharpe ratio. Its much lower volatility is especially advantageous when considering the multiplication of volatility experienced when gearing is applied to a long-short strategy. Margins could be under severe pressure if a sizable drawdown is experienced with a geared portfolio, a situation that is more likely when using a conventional momentum strategy as opposed to a residual momentum strategy. A residual momentum style geared to provide similar volatility to that of conventional momentum would have provided greater returns over the time period studied.

6.2 Discussion Concerning Research Question 2

Research Question Two concerned the effect of investor sentiment on momentum in the South African market. The comparison of this effect on residual momentum and conventional momentum was of interest for both practical as well as academic reasons.

Excess investor sentiment was determined across the time series and discrete investor sentiment states were defined based on this variable. The mean returns of portfolios formed during different investor sentiment states were investigated. Additionally, returns during different investor sentiment state holding periods were analysed.

6.2.1 Investor Sentiment Proxy

The investor sentiment proxy utilised was crucial to the investigation of the effect of investor sentiment on momentum returns. The theoretical basis and validity of the construct was discussed in sections 4.6 and 4.9.2.

The time-series of investor sentiment as depicted in Figure 5 matched anecdotal evidence of significant events in the South African market. Sentiment was low during the uncertain times prior to South Africa's first democratic election. Other low points followed significant events in international markets such as the internet bubble of the early 2000s and the sub-prime crisis of 2008 (Baker & Wurgler, 2007; Beer & Zouaoui, 2013; Solanki & Seetharam, 2014).

An important observation from this time-series of data (Figure 5, Figure 6, and Figure 7) was the persistent positive sentiment state in the three years prior to the 2008/2009 recession. In fact, this period contributed thirteen of the 22 quarters with optimistic formation periods. It was critical to be mindful of this period and its effect on the data when analysing investor sentiment's effect on returns obtained through momentum strategies.

Analyses were conducted using the CCI orthogonalised to macroeconomic variables and, separately, the raw CCI. The results proved to be similar, indicating a level of robustness to the choice of investor sentiment proxy. The discussion below was therefore limited to the results of the analysis with investor sentiment proxied by the orthogonalised CCI and not the raw CCI. This followed international precedence found in the literature (Antoniou et al., 2013; Lemmon & Portniaguina, 2006).

6.2.2 Residual and Conventional Momentum Returns following different Formation Period Sentiment States

The primary focus of this section of the research was on the effect of investor sentiment on residual momentum. However, the effect of investor sentiment on conventional momentum was discussed first in order to compare the results obtained to that presented in international literature and the theoretical implications thereof. This was followed by a discussion of investor sentiment's effect on residual momentum.

The discussion below considers the results for an investor sentiment state definition utilising the 20th/80th percentile break points as provided in Table 12. Any reference to results using different sentiment break points was reported as such. Ultimately the results were similar despite the choice of sentiment state break points.

6.2.2.1 Investor Sentiment and Conventional Momentum

While the results for conventional momentum did not allow for formal statistical inferences to be made, returns did appear greater following neutral and optimistic formation periods than following pessimistic formation periods.

Theory and previous research indicated that shares in the loser (winner) portfolios become overpriced (underpriced) during periods of positive (negative) sentiment due to the slow rate of diffusion of news (Hong & Stein, 1999), especially news that contradicts the prevailing sentiment, due to cognitive dissonance (Antoniou et al., 2013). The effect is exacerbated by limits to arbitrage (Antoniou et al., 2013; Shleifer & Vishny, 1997). Short selling constraints, one of the main limits to arbitrage, make it more difficult to arbitrage away the overpricing in loser stocks and this leads to profits mainly after optimistic periods. Following the high sentiment period, these loser stocks then revert strongly to more reflective pricing and show low returns during the holding period.

Another explanation not explicitly found in international research on the effect of investor sentiment on momentum is the effect of investor sentiment on speculative stocks and the resultant impact on momentum portfolio construction and subsequent returns. Small, young, difficult-to-value and difficult-to-arbitrage stocks are most vulnerable to changes in investor sentiment (Baker & Wurgler, 2006). However, the effect is not uniform across sentiment states. Baker and Wurgler (2006) noted that factors, such as size and certain value indicators, only appear to exhibit their effect (Banz, 1981; Basu, 1977) after periods of negative sentiment. This meant that the conventional momentum loser portfolio would likely contain underperforming and underpriced speculative stocks following pessimistic formation periods. The very nature of these stocks acts as a limit to arbitrage. The loser portfolio then provides higher than expected returns during the holding period and reduces the profits of the momentum strategy.

The conventional momentum results supported the above hypotheses to a certain extent. Firstly, mean profits post pessimistic formation periods were consistently the lowest. Sentiment-based mispricing in stock prices led to stocks likely being underpriced. However, considering literature-based explanations, this potential underpricing was arbitraged away quickly as it required the arbitrageur simply to buy the stocks (Antoniou et al., 2013; Hühn & Scholz, 2016). The low return of the winner portfolio was consistent with this explanation. In addition, the relatively high return on the bottom portfolio was consistent with the notion that during pessimistic formation periods the loser portfolio became loaded with underpriced, speculative and difficult-to-arbitrage stocks which provided strong returns when the mispricing reversed during the holding period.

Additionally, profits were significant during periods of neutral sentiment. The effect of sentiment was limited during this period, but the behavioural biases causing momentum remained. Antoniou et al. (2013) went further and ascribed the profitability of momentum following neutral formation periods to the notion that neutral periods were in fact slightly optimistic. They also refer to these periods not as neutral, but as mild.

The highest average profits were not achieved following optimistic formation periods as would be expected based on other empirical studies (Antoniou et al., 2013; Hühn & Scholz, 2016; Stambaugh et al., 2012). The results (Table 12) revealed that the profitability of returns following optimistic formation periods was impacted by excessive returns experienced by the loser portfolio in comparison to international studies (Antoniou et al., 2013; Stambaugh et al., 2012). The anomalous response could be ascribed to the high levels of serial correlation in investor sentiment. Particularly the fact that the entire period between March 2005 and April 2008 was ranked as being optimistic based on the weighted average formation sentiment levels. This was also the period with the most consistent sentiment levels (monthly standard deviation, $\sigma = 2.15$) over the total time series ($\sigma = 8.31$). Overpricing of the loser stocks was therefore sustained for a long period as optimistic period repeatedly followed optimistic period with reversals only evident when sentiment levels eventually changed. Returns following optimistic periods were likely impacted by contemporaneous sentiment induced over- or underpricing.

A further possible source of disparities in the results was likely related to methodological differences. Antoniou et al. (2013) used monthly-formed, overlapping portfolios and determined the overall sentiment state by considering the formation sentiment state of all portfolios held at the time. This provided an element of contemporaneous sentiment, especially for portfolios formed earlier as the formation periods of the more recent portfolios include the holding periods of earlier portfolios. This study used quarterly formed portfolios which were only held for a single quarter. No portfolios overlapped, and the investor sentiment state during the formation period of the portfolio held was clearly isolated.

Overall, the effect of investor sentiment on conventional momentum was inconclusive, but did hint towards results similar to that found in international studies. Pessimistic formation periods were likely to lead to lower profits than neutral or optimistic formation periods. The theory behind the results all consider likely over- and underpricing due to behavioural finance effects and the correction of this sentiment-induced mispricing during the holding period. The lower than expected returns following optimistic periods did not disprove the theory, as the low returns were due to the sentiment staying high for a long time with the resultant mispricing persisting during this period.

6.2.2.2 Investor Sentiment and Residual Momentum

Residual momentum delivered its lowest profits following optimistic investor sentiment states and its highest profits following pessimistic sentiment states.

The significant profits for the residual momentum strategy following periods with low investor sentiment were mainly driven by higher returns in the winner portfolio. This was consistent with the theories of cognitive dissonance explaining the effect of investor sentiment and under-reaction explaining residual momentum. The winner portfolio's stocks became underpriced during the pessimistic formation period due to slow investor reaction to positive idiosyncratic news. The pricing error was corrected during the holding period, leading to excess profits. Residual momentum's key aspect of market under-reaction to firm-specific news acted as to a limit to arbitrage. Arbitrageurs only reacted belatedly to firm specific good news, especially following pessimistic periods as news diffusion across the market was slowed due to cognitive dissonance. This allowed for the underpricing of stocks to persist long enough for subsequent correction of this mispricing to occur during the portfolio holding period. The conventional momentum strategy was exposed to the same phenomenon, but the same effect was not evident. Limits to arbitrage associated with underpriced stocks are generally quite low (Antoniou et al., 2013; Baker & Wurgler, 2007; Shleifer & Vishny, 1997), and without the under-reaction phenomenon, potential underpricing of the winner portfolio was arbitraged away immediately.

Residual momentum failed to show significant profits following optimistic formation periods. The high returns of the winner portfolio were mostly negated by the high returns of the loser portfolio. Discussions of this result again had to consider the large number of consecutive optimistic quarters. The results were likely impacted by a contemporaneous investor sentiment effect. This assumption was supported by similarly high returns for the residual momentum loser portfolio during optimistic holding periods (Table 16). With this in mind, the results were consistent with the argument of cognitive dissonance slowing the reaction of investors to news that belie their current sentiment and beliefs (Antoniou et al., 2013; Daniel et al., 1998). The loser stocks' associated overpricing was worsened by short selling constraints and other limits to arbitrage.

To summarise, investor sentiment was shown to affect the profitability of residual momentum strategies. Cognitive dissonance was again the main theoretical driver behind the effect where news, counter to prevailing sentiment, diffuses slowly leading to mispricing which is corrected in the holding periods following portfolio formation. However, where conventional momentum profits were not significant following pessimistic periods due to effective arbitrage, the under-reaction phenomenon behind residual momentum slowed the news diffusion, especially of good news regarding winner stocks during pessimistic periods, even further. The correction of the underpricing error was thus delayed enough for the residual momentum investor to capture the returns during the holding period following pessimistic formation periods.

From a practical perspective, conventional momentum ultimately provided superior returns after optimistic and neutral periods, while residual momentum proved to be superior following periods of pessimistic sentiment. A combined strategy bringing in an element of timing based on investor sentiment levels could presumably improve total returns. The results of such a strategy were provided in Table 15. The strategy compared favourably to strategies employing only conventional or residual momentum and highlighted the practical benefits of incorporating investor sentiment into momentum investment strategies. The combined style provided higher cumulative returns and greater average annual returns than either of the individual styles. The combined strategy also provided these returns at a higher Sharpe ratio than the individual momentum styles. Investor sentiment could thus be used to help avoid significant conventional momentum crashes (Barroso & Santa-Clara, 2015; Daniel & Moskowitz, 2013) by rather using residual sentiment, which was relatively robust to crashes, after periods of severely negative sentiment. It must be noted that these results were obtained on only in-sample data and have not been verified using out-of-sample data. The strategy proposed above requires further investigation and any application thereof must be approached with caution.

6.2.3 Residual and Conventional Momentum Returns during different Holding Period Sentiment States

The effect of investor sentiment during the holding period of momentum strategies on said strategies was investigated for academic purposes only. It had little practical purpose as it would require prescient knowledge of future investor sentiment levels to apply the results to practical investment strategies.

Investor sentiment appeared to have had little contemporaneous effect on either momentum style. Conventional momentum proved profitable across the different holding period sentiment states, with no significant differences between mean returns conditional on sentiment states. Residual momentum also provided significant returns, at an alpha level of 0.05, across all sentiment states. Mean profits were the highest during neutral periods, but the differences between returns during this and other sentiment states were not significant.

While Brown and Cliff (2004, 2005) and Baker and Wurgler (2007) noted a significant correlation between sentiment and concomitant market returns, Solanki and Seetheram (2014) found only weak evidence of a concomitant effect between the CCI and market returns on the JSE.

The lack of effect found in this study likely related to the fact that the returns were observed on portfolios formed prior to the holding period and its associated level of investor sentiment. Formation period sentiment affected the formation of portfolios, possibly leading to biased portfolios. In contrast, sentiment during the holding period likely affected individual stocks, but the affected stocks were spread across the winner and loser portfolios. Sentiment based effects were thus averaged out between the long and short legs of the investment.

7 Conclusion

7.1 Theoretical and Practical Implications

The study investigated, firstly, the applicability of a residual momentum style on the JSE and how this compared to a conventional momentum style. Secondly, the effect of investor sentiment on both styles was explored in order to gain an understanding of the theoretical underpinnings of these stock market phenomena and to investigate the possibility of a practical investment style conditioning momentum on investor sentiment.

Residual momentum referred to a momentum style that considers only firm-specific returns in the construction of its portfolios by disregarding returns associated with common risk factors. Residual momentum was indeed found to be a viable style on the JSE, providing significant excess returns over the past 27 years on the JSE. While residual momentum underperformed conventional momentum in terms of cumulative returns over the time period studied, it did so while experiencing much lower volatility and significantly less drawdown. Residual momentum also appeared to be more robust to market volatility and less likely to experience momentum crashes (Barroso & Santa-Clara, 2015; Daniel & Moskowitz, 2013). Ultimately, residual momentum's risk-adjusted returns were greater than that of conventional momentum, confirming international results (Blitz et al., 2011; Gutierrez & Pirinsky, 2007).

Academically, the study was the first to investigate residual momentum on the JSE. It also determined optimal formation and holding periods in this market, albeit without consideration of transaction costs. The results showed that residual momentum react similarly to international markets (Blitz et al., 2011; Gutierrez & Pirinsky, 2007), despite the JSE's structural, size and liquidity differences.

Practically, an investor interested in pursuing a momentum investment style, but hesitant in taking on the associated volatility would be better served by following a residual momentum style. Alternatively, its lower drawdown risk allows for more aggressive gearing ratios in a zero-investment strategy. The lower Sharpe ratio meant that a residual momentum strategy would provide greater returns than a conventional momentum strategy if geared to an equivalent volatility level.

The level of **investor sentiment** during the portfolio formation period did appear to have an effect on the returns of residual momentum as well as conventional momentum.

However, the styles were affected in different manners, allowing for interesting academic observations and practical opportunities.

Academically, the study was the first to investigate the effect of investor sentiment on momentum on the JSE. It was also globally one of the first to consider the effect of investor sentiment on residual momentum. The results for conventional momentum were consistent with theoretical explanations put forth by authors such as Antoniou et al.'s (2013) cognitive dissonance hypothesis. Residual momentum responded in a different manner than conventional momentum to investor sentiment, but it was still consistent with the cognitive dissonance explanation when the under-reaction phenomenon (Blitz et al., 2011) behind residual momentum was taken into account.

Practically, the disparities in residual and conventional momentum returns when conditioned on investor sentiment allows for a dynamic investment strategy that utilises investor sentiment to optimise the returns of momentum investing styles. In-sample testing showed that a simple strategy selecting between momentum styles depending on the level of investor sentiment indeed provided higher returns and an improved Sharpe ratio.

7.2 Limitations and Recommendations for Future Research

The study set out to examine the concept of residual momentum on the JSE, comparing it to conventional momentum and to consider how both of these momentum styles were affected by investor sentiment. The study was subject to various limitations, but these, together with the encouraging results obtained, served to strengthen the case and provide opportunities for future research into the subject.

The concept of residual momentum showed a risk-adjusted improvement over conventional momentum on the JSE, warranting further investigation. Future research into this topic could include the effect of transaction costs or consider residual momentum's applicability to other asset classes. Alternative asset pricing models such as Carhart's (1997) four factor model, Fama and French's (2015) modified five factor model or an arbitrage pricing theory model considering different factors could be used to determine residual momentum and to test whether the results hold.

The use of investor sentiment as a market timing tool to improve momentum investing also showed potential merits and could hold great practical implications. Further investigation and out-of-sample testing in this area is warranted by the results of this study. The use of alternative sentiment indicators, such as a Baker-Wurgler type index (Baker & Wurgler, 2007) or other survey based indices, could also augment the results of the study.

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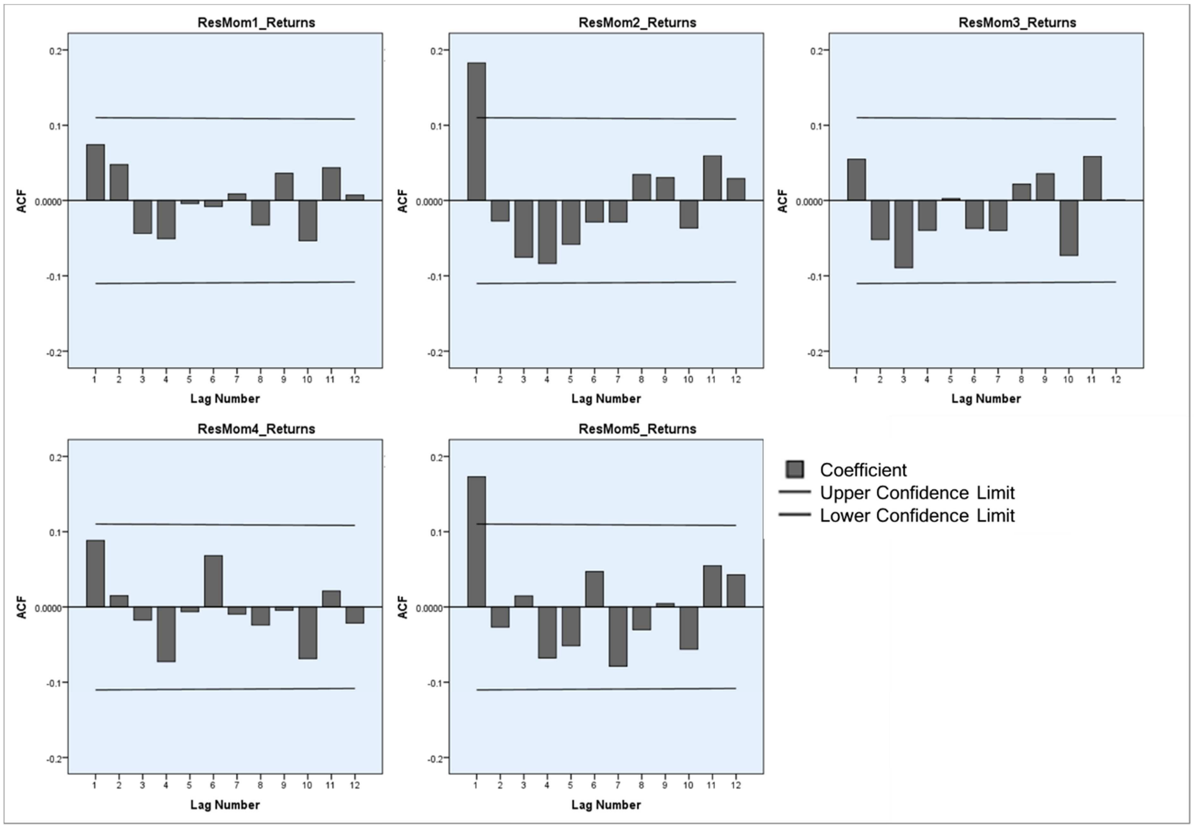
Appendix 1. Additional Results for Section 5.1

Autocorrelation test results for residual momentum portfolios using monthly returns data (section 5.1.3)

Figure 8: Correlograms for Residual Momentum Portfolios based on Monthly Returns



Kolmogorov-Smirnov test for equal distributions of residual momentum portfolios using monthly returns data (section 5.1.3)

Table 19: Kolmogorov-Smirnov Test Results for Residual Momentum Portfolios Monthly Returns Data

		Test Statistic	Significance (2-sided)
Residual Momentum Portfolio 5	Residual Momentum Portfolio 4	[-1.056]	.215
	Residual Momentum Portfolio 3	[-1.369]	.047*
	Residual Momentum Portfolio 2	[-1.408]	.038*
	Residual Momentum Portfolio 1	[-1.525]	.019*
Residual Momentum Portfolio 4	Residual Momentum Portfolio 3	[-0.665]	.769
	Residual Momentum Portfolio 2	[-0.782]	.574
	Residual Momentum Portfolio 1	[-1.056]	.215
Residual Momentum Portfolio 3	Residual Momentum Portfolio 2	[-0.665]	.769
	Residual Momentum Portfolio 1	[-0.978]	.295
Residual Momentum Portfolio 2	Residual Momentum Portfolio 1	[-1.095]	.182

*. The difference is significant at the 0.05 level

Jonckheere-Terpstra test on residual momentum portfolios using *bimonthly* returns data (section 5.1.3)

This test showed that there was a statistically significant trend, at a significance level of .05, of higher returns associated with portfolios created based on higher residual returns, $T_{JT}(815) = -2.607$, $p = .009$. The null hypothesis was therefore rejected and the alternate hypothesis accepted.

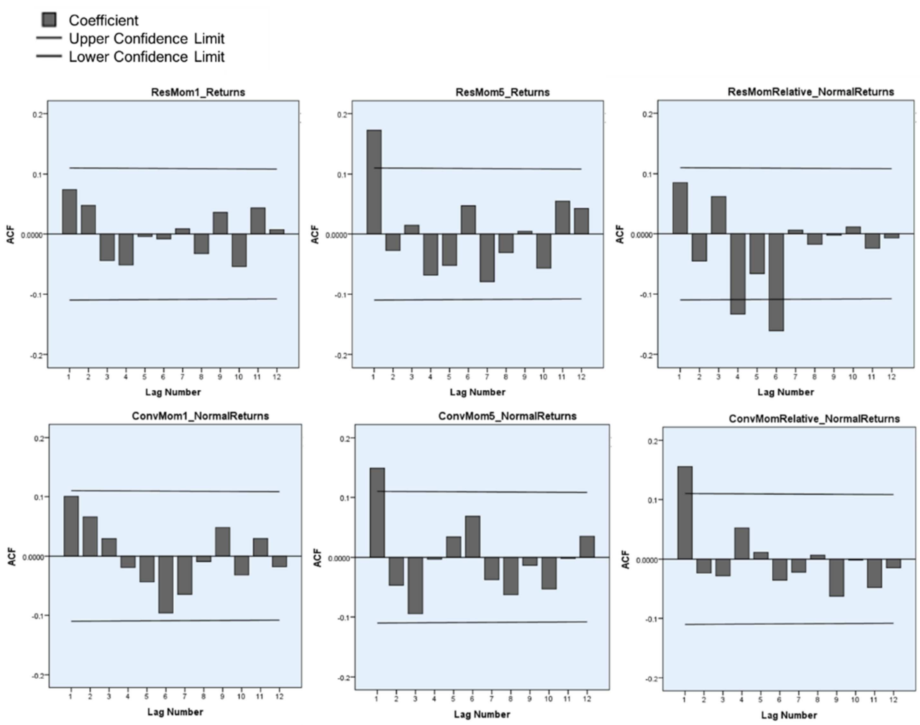
Table 20: Pairwise Comparison Post Hoc Analysis of Residual Return Portfolios using Bimonthly Returns with Bonferroni-adjusted Significance Values

		Test Statistic	Standardised Test Statistic	Significance (1-sided)	Adjusted Significance (1-sided)
Residual Momentum Portfolio 5	Residual Momentum Portfolio 4	11881	[-1.649]	.050	.495
	Residual Momentum Portfolio 3	11766	[-1.785]	.037	.372
	Residual Momentum Portfolio 2	11584	[-1.999]	.023	.228
	Residual Momentum Portfolio 1	**10999**	**[-2.686]**	**.004**	**.036***
Residual Momentum Portfolio 4	Residual Momentum Portfolio 3	13138	[-0.172]	.432	1.000
	Residual Momentum Portfolio 2	12976	[-0.363]	.358	1.000
	Residual Momentum Portfolio 1	12278	[-1.183]	.118	1.000
Residual Momentum Portfolio 3	Residual Momentum Portfolio 2	13485	[0.236]	.407	1.000
	Residual Momentum Portfolio 1	12370	[-1.075]	.141	1.000
Residual Momentum Portfolio 2	Residual Momentum Portfolio 1	12456	[-0.974]	.165	1.000

*. The difference is significant at the 0.05 level

<u>Autocorrelation test results for residual and conventional momentum portfolios using monthly returns data (section 5.1.5)</u>

Figure 9: Correlograms for Residual and Conventional Momentum Portfolios based on Monthly Returns



Kolmogorov-Smirnov test for equal distributions of residual momentum portfolios using monthly returns data (section 5.1.5)

Table 21: Kolmogorov-Smirnov Test Results for Residual Momentum Portfolios Monthly Returns Data

		Test Statistic	Significance (2-sided)
Residual Momentum Portfolio 1	Conventional Momentum Portfolio 1	[0.743]	.639
Residual Momentum Portfolio 5	Conventional Momentum Portfolio 5	[0.860]	.450
Residual Momentum Portfolio 1 - 5	Conventional Momentum Portfolio 1 - 5	[1.760]	.004*

*. The difference is significant at the 0.05 level

Mann-Whitney U-test for differences using *bimonthly* returns data (section 5.1.5)

Table 22: Mann-Whitney U-test using Bimonthly Returns Data

		Test Statistic	Standardised Test Statistic	Significance (2-sided)
Residual Momentum Portfolio 1	Conventional Momentum Portfolio 1	14453	[1.373]	.170
Residual Momentum Portfolio 5	Conventional Momentum Portfolio 5	12844	[-0.518]	.605
Residual Momentum Portfolio 1 - 5	Conventional Momentum Portfolio 1 - 5	14338	[1.238]	.216

Appendix 2. Additional Results for Section 5.2

CCI regression model – betas and significance values of macroeconomic variables (section 5.2.1)

Table 23: CCI Regression Model Predictor Significance

	Beta	Significance
(Constant)	-1.20	.431
GDP Growth	17.27	.000
Employment Growth	-5.17	.006
Inflation	0.43	.669
Bond Yield	0.06	.647
Industrial Production Growth	-0.02	.918

Assumption tests for portfolio returns comparison based on formation period investor sentiment and using $30^{th}/70^{th}$ percentile break points (section 5.2.2)

Table 24: Tests of Assumptions for Formation Period Sentiment with $30^{th}/70^{th}$ Percentile Break Points

		Shapiro-Wilk			Durbin-Watson		
Dependent Variable		df	Statistic	Sig.	D	L-L	U-L
Residual Momentum	Portfolio 1	109	0.977	.056	1.937	1.715	2.285
	Portfolio 5	109	0.993	.889	1.954	1.715	2.285
	Portfolio 1 - 5	109	0.982	.157	2.208	1.715	2.285
Conventional Momentum	Portfolio 1	109	0.932	.000	1.824	1.715	2.285
	Portfolio 5	109	0.975	.035	2.183	1.715	2.285
	Portfolio 1 - 5	109	0.967	.008	2.079	1.715	2.285
Market	ALSI (J203)	109	0.982	.137	2.043	1.715	2.285

Assumption tests for portfolio returns comparison based on formation period investor sentiment and using 15th/85th percentile break points (section 5.2.2)

Table 25: Tests of Assumptions for Formation Period Sentiment with 15th/85th Percentile Break Points

Dependent Variable		Shapiro-Wilk df	Shapiro-Wilk Statistic	Shapiro-Wilk Sig.	Durbin-Watson D	Durbin-Watson L-L	Durbin-Watson U-L
Residual Momentum	Portfolio 1	109	0.976	.048	1.968	1.715	2.285
	Portfolio 5	109	0.994	.901	1.979	1.715	2.285
	Portfolio 1 - 5	109	0.983	.176	2.182	1.715	2.285
Conventional Momentum	Portfolio 1	109	0.918	.000	1.873	1.715	2.285
	Portfolio 5	109	0.973	.024	2.196	1.715	2.285
	Portfolio 1 - 5	109	0.979	.090	2.079	1.715	2.285
Market	ALSI (J203)	109	0.974	.033	2.060	1.715	2.285

Assumption tests for portfolio returns comparison based on holding period investor sentiment and using 20th/80th percentile break points (section 5.2.3)

Table 26: Tests of Assumptions for Holding Period Sentiment with 20th/80th Percentile Break Points

Dependent Variable		Shapiro-Wilk df	Shapiro-Wilk Statistic	Shapiro-Wilk Sig.	Durbin-Watson D	Durbin-Watson L-L	Durbin-Watson U-L
Residual Momentum	Portfolio 1	108	0.977	.055	1.911	1.715	2.285
	Portfolio 5	108	0.992	.780	1.948	1.715	2.285
	Portfolio 1 - 5	108	0.984	.217	2.190	1.715	2.285
Conventional Momentum	Portfolio 1	108	0.929	.000	1.865	1.715	2.285
	Portfolio 5	108	0.972	.022	2.077	1.715	2.285
	Portfolio 1 - 5	108	0.968	.010	2.002	1.715	2.285
Market	ALSI (J203)	108	0.978	.069	2.073	1.715	2.285

Assumption tests for portfolio returns comparison based on holding period investor sentiment and using 30th/70th percentile break points (section 5.2.3)

Table 27: Tests of Assumptions for Holding Period Sentiment with 30th/70th Percentile Break Points

		Shapiro-Wilk			Durbin-Watson		
Dependent Variable		**df**	**Statistic**	**Sig.**	**D**	**L-L**	**U-L**
Residual Momentum	Portfolio 1	108	0.972	.020	1.954	1.715	2.285
	Portfolio 5	108	0.995	.972	1.979	1.715	2.285
	Portfolio 1 - 5	108	0.981	.133	2.206	1.715	2.285
Conventional Momentum	Portfolio 1	108	0.930	.000	1.867	1.715	2.285
	Portfolio 5	108	0.977	.058	2.117	1.715	2.285
	Portfolio 1 - 5	108	0.969	.012	2.007	1.715	2.285
Market	ALSI (J203)	108	0.976	.071	2.111	1.715	2.285

Assumption tests for portfolio returns comparison based on holding period investor sentiment and using 15th/85th percentile break points (section 5.2.3)

Table 28: Tests of Assumptions for Holding Period Sentiment with 15th/85th Percentile Break Points

		Shapiro-Wilk			Durbin-Watson		
Dependent Variable		**df**	**Statistic**	**Sig.**	**D**	**L-L**	**U-L**
Residual Momentum	Portfolio 1	108	0.973	.023	1.911	1.715	2.285
	Portfolio 5	108	0.993	.877	1.948	1.715	2.285
	Portfolio 1 - 5	108	0.983	.173	2.190	1.715	2.285
Conventional Momentum	Portfolio 1	108	0.927	.000	1.865	1.715	2.285
	Portfolio 5	108	0.971	.019	2.077	1.715	2.285
	Portfolio 1 - 5	108	0.970	0.14	2.002	1.715	2.285
Market	ALSI (J203)	108	0.976	0.48	2.073	1.715	2.285

Assumption tests for portfolio returns comparison based on formation period investor sentiment proxied by the raw CCI and using 20th/80th percentile break points (additional analysis based on section 5.2.2)

Table 29: Tests of Assumptions for Formation Period Sentiment using CCI with 20th/80th Percentile Break Points

Dependent Variable		df	Shapiro-Wilk Statistic	Sig.	Durbin-Watson D	L-L	U-L
Residual Momentum	Portfolio 1	109	0.972	.019	1.997	1.715	2.285
	Portfolio 5	109	0.992	.817	2.006	1.715	2.285
	Portfolio 1 - 5	109	0.981	.126	2.182	1.715	2.285
Conventional Momentum	Portfolio 1	109	0.924	.000	1.897	1.715	2.285
	Portfolio 5	109	0.975	.038	2.228	1.715	2.285
	Portfolio 1 - 5	109	0.974	.030	2.092	1.715	2.285
Market	ALSI (J203)	109	0.975	.035	2.096	1.715	2.285

Results of portfolio returns comparison based on formation period investor sentiment proxied by the raw CCI and using 20th/80th percentile break points (additional analysis based on section 5.2.2)

Table 30: Mean Quarterly Returns Conditional on Investor Sentiment as per CCI during Formation Period (20th/80th Percentile Break Points)

		Residual Momentum Portfolios					Conventional Momentum Portfolios					Market (ALSI)		
State	n	Loser	Winner	Relative	t-stat	Sig.	Loser	Winner	Relative	t-stat	Sig.	J203	t-stat	Sig.
Mean profits following different sentiment states:														
Optimistic	(22)	**4.82**	7.18	2.44	[2.15]	.031	4.85	8.97	4.25	[2.53]	.012	6.59	[4.36]	.000
Neutral	(63)	1.38	5.12	**4.09**	[4.77]	.000	0.66	6.34	6.44	[4.25]	.000	3.31	[3.19]	.001
Pessimistic	(24)	1.74	6.01	**4.91**	[3.24]	.001	2.67	4.97	4.12	[1.25]	.211	3.79	[1.48]	.138
Statistical comparison of mean profits following different sentiment states:														
Optimistic-Pessimistic		3.08		**-2.47**										
t-stat		[0.93]		[-1.30]										
Sig.		.351		.192										

Assumption tests for portfolio returns comparison based on holding period investor sentiment proxied by the raw CCI and using 20th/80th percentile break points (additional analysis based on section 5.2.3)

Table 31: Tests of Assumptions for Holding Period Sentiment using CCI with 20th/80th Percentile Break Points

Dependent Variable		df	Shapiro-Wilk Statistic	Shapiro-Wilk Sig.	Durbin-Watson D	Durbin-Watson L-L	Durbin-Watson U-L
Residual Momentum	Portfolio 1	108	0.975	.037	2.003	1.715	2.285
	Portfolio 5	108	0.992	.800	2.000	1.715	2.285
	Portfolio 1 - 5	108	0.987	.376	2.144	1.715	2.285
Conventional Momentum	Portfolio 1	108	0.923	.000	1.908	1.715	2.285
	Portfolio 5	108	0.966	.007	2.204	1.715	2.285
	Portfolio 1 - 5	108	0.973	.024	2.065	1.715	2.285
Market	ALSI (J203)	108	0.975	.039	2.096	1.715	2.285

Results of portfolio returns comparison based on holding period investor sentiment proxied by the raw CCI and using 20th/80th percentile break points (additional analysis based on section 5.2.3)

Table 32: Mean Quarterly Returns Conditional on Investor Sentiment as per CCI during Holding Period (20th/80th Percentile Break Points)

		Residual Momentum Portfolios					Conventional Momentum Portfolios					Market (ALSI)		
State	n	Loser	Winner	Relative	t-stat	Sig.	Loser	Winner	Relative	t-stat	Sig.	J203	t-stat	Sig.
Mean profits during different sentiment states:														
Optimistic	(22)	**5.42**	7.80	**2.42**	[2.13]	.033	4.60	9.67	4.95	[3.75]	.000	6.35	[4.92]	.000
Neutral	(65)	0.77	5.32	**5.04**	[5.41]	.000	0.41	6.10	6.61	[3.81]	.003	3.29	[2.58]	.010
Pessimistic	(21)	2.79	4.91	**2.45**	[2.24]	.025	3.55	4.98	3.03	[1.18]	.015	4.05	[2.24]	.025
Statistical comparison of mean profits during different sentiment states:														
Optimistic-Pessimistic		2.64		-0.28										
t-stat		[1.01]		[-0.18]										
Sig.		.178		.986										

Appendix 3. Ethical Clearance

Dear Mr Louis Viljoen

Protocol Number: **Temp2016-01160**

Title: **Residual momentum and investor sentiment on the JSE**

Please be advised that your application for Ethical Clearance has been APPROVED.

You are therefore allowed to continue collecting your data.

We wish you everything of the best for the rest of the project.

Kind Regards,

Adele Bekker