University of the Western Cape

FACULTY OF

ECONOMIC AND MANAGEMENT SCIENCES

CYCLICALITY OF SIZE, VALUE, AND MOMENTUM ON THE JOHANNESBURG STOCK EXCHANGE

BY

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This thesis is written under the supervision of Dr. Warren Brown and submitted in full fulfilment of the requirements for the Degree of Master of Commerce in Finance in the School of Business and Finance of the Faculty of Economic and Management Sciences at the University of the Western Cape.

November 2019

Declaration

I, Kapche Fotso Moïse Hervé, hereby declare that this thesis, titled Cyclicality of Size, Value, and Momentum on the Johannesburg Stock Exchange, is my own original work, and has not been previously submitted for any degree or any examination at this university or any other university or institution. All sources used or quoted therein have been duly acknowledged.

Kapche Fotso Moïse Hervé

November 2019

Dedication

I dedicate this thesis to my beloved family

Acknowledgements

I express my gratitude to my academic supervisor, Dr. Warren Brown, for having made me benefited from his technical skills and expertise, as well as from his pieces of advice. He has really enriched my work and motivated me through encouragements.

I warmly thank my former supervisor, Prof. Kathleen Hodnett, for her invaluable guidance and support during the first year of my thesis writing and thereafter. I equally extend my thanks to Prof. Heng-Hsing (Andy) Hsieh for his insightful comments.

Special thanks go to Prof. Lorna Holtman, who has provided me with unwavering assistance in navigating the psychological and financial strains that I had to deal with during the writing of this thesis.

Many thanks are due to the National Research Foundation (NRF), which provided me with the funding necessary to complete this thesis.

I equally express my profound gratitude to the JSE Limited for their valuable assistance in collecting the data I needed to complete my thesis.

I sincerely thank my family and friends for their moral support and encouragements each time I felt overwhelmed by the workload necessary to complete this thesis.

Lastly but not least, I extend my special thanks to my colleagues and staff in the School of Business and Finance, and to staff members of the University of the Western Cape who directly and indirectly contributed to the completion of this thesis.

Abstract

Over the past four decades, size, value and momentum effects have been uncovered on stock markets, and several multifactor asset pricing models have been proposed to explain them. The associated premiums have been found to be time-varying and the explanations behind the effects are still debated. In South Africa, contradictory findings have been reported on the existence of those effects and the explanatory power of multifactor models. More important, the cyclicality of the effects and the risk/mispricing debate have been given little attention.

In this regard, this study purports to establish the existence of size, value and momentum effects, investigate the explanatory power of the Fama-French three- and five-factor models (FF3F and FF5F respectively), and Carhart four-factor model (C4F), and examine the cyclicality and risk-based rationale of the style premiums on the Johannesburg Stock Exchange (JSE). Using a research sample comprised of common stocks included in the FTSE/JSE All Share Index (ALSI) for the period 1 January 2002 - 31 December 2018, the study subdivides the examination period into two business cycles, with each cycle including one upward phase and one downward phase.

Results reveal that while size, value and momentum effects are present on the JSE over the examination period, an attenuation, disappearance, or reversal of the size effect is reported during the downward phases of the business cycle, whereas a strengthening of the value effect is reported for those phases. Lastly, a weakening of the momentum effect is equally observed during downward periods. Besides, the FF3F, C4F and FF5F are reliable predictors of stock returns on the JSE, and are more accurate than the CAPM in explaining returns. Nevertheless, these models do not fully explain stock returns, reflecting the need for more efficient models. Furthermore, the results of this study uncover a cyclical trend in the size, value and momentum effects on the JSE. The size and momentum premiums are procyclical as they tend to increase during upward periods and decrease during downward periods. Conversely, the value premium is countercyclical since it rises during downward periods. Finally, the study results uncover, to some extent, a risk-based explanation for the style effects on the JSE over the examination period. In effect, the exposure of the factor premiums to systematic risk tends to amplify during downward periods, when the market is more volatile. Conversely, the exposure attenuates during upward periods.

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List of Abbreviations

ACAR: average cumulative abnormal return

ALSI: All-Share Index

APT: Arbitrage Pricing Theory

BE/ME: book-to-market equity

B/M: book-to-market (ratio)

B/P: book-to-price (ratio)

C4F: Carhart four-factor model

CAPM: Capital Asset Pricing Model

CAR: cumulative average return

CMA: conservative minus aggressive

CML: capital market line

C/P: cash-flow-to-price (ratio)

D/P: dividend-to-price (ratio)

D/Y: dividend yield

EAFE: Europe, Australia, and the Far East

EMH: Efficient Market Hypothesis

E/P: earnings-price (ratio)

EUT: expected utility theory

FF3F: Fama-French three-factor model

FF5F: Fama-French five-factor model

FTSE: Financial Times Stock Exchange

HML: high minus low

JSE: Johannesburg Stock Exchange

LSE: London Stock Exchange

MOM: momentum

MPT: Modern Portfolio Theory

NYSE: New York Stock Exchange

OLS: ordinary least squares

P/CF: price-to-cash-flow (ratio)

P/E: price-earnings (ratio)

RMW: robust minus weak

SARB: South African Reserve Bank

SETS: Securities Exchange Trading System

SMB: small minus big

SML: security market line

S/P: sales-to-price (ratio)

WML: winners minus losers

CHAPTER 1 – INTRODUCTION

1.1 Research Background

The concept of market anomalies has inspired a large volume of research in the finance discipline, since the evidence of whether they are present or not on capital markets has direct and significant implications for the efficiency of financial markets. Indeed, market efficiency is a core concept in finance and it heavily influences investment strategies of investors and asset managers on financial markets, depending on whether they believe that the market is efficient or not. Market efficiency refers to the belief that asset prices observed in the market reflect the intrinsic value of the assets as they incorporate all the relevant information pertaining to the assets in question. A major implication of this concept is that returns generated in the market are commensurate to the risk borne by investors, and this risk-return relationship has been traditionally tested using the Capital Asset Pricing Model (CAPM). Thus, market anomalies refer to risk-return relationships not explained by the CAPM, and they are perceived either as compensation for higher risk undertaken or as a result of mispricing of assets. Therefore, a comprehensive understanding of this study necessitates the definition of a background context related to theories and concepts that led to the identification of market anomalies on financial markets and thereafter.

The concept of market efficiency (and eventually market anomalies) is rooted in the random walk theory, which contends that asset prices vary following an irregular pattern. Early works of Regnault (1863) and Bachelier (1900) on the French stock market uncover no correlation between past and present stock prices, implying that it is not possible to predict future prices by analysing past trends in stock prices. Kendall (1953) officially introduces the random walk theory following a study on the U.S. stock market. The author analyses movements in prices of stock indices and commodities in the U.S. and finds a weak correlation between successive weekly price fluctuations. Current asset prices vary independently from prior prices and, consequently, it is not possible to predict future prices from past data.

Fama (1965) equally investigates stock price patterns on financial markets in order to uncover additional evidence supporting the random walk of stock prices. His study reveals that except for major price movements which seem to provoke subsequent major movements, the relationship between past and future prices is generally weak. These findings are consistent with Kendall's (1953). Five years later, Fama (1970) proposes his today's widely known Efficient Market Hypothesis (EMH). The EMH builds on the random walk hypothesis and posits that information available on financial markets is already embedded in current asset prices. The main implication of this Hypothesis is that using information available on the market to generate abnormal returns consistently on a risk-adjusted basis is a myth. Fama (1970) equally specifies that tests on the validity of the EMH should be done using an equilibrium model, such as the CAPM. This condition, known as the Joint Hypothesis, later gives rise to the formulation of the Joint Hypothesis problem, referring to the fact that market efficiency cannot be tested because it would be difficult to disentangle a model misspecification issue from market inefficiency itself (Fama, 1991).

The CAPM, which is central to testing the validity of EMH, originates from Markowitz's (1952) Modern Portfolio Theory (MPT), considered to have laid down the foundations of modern finance. Indeed, assuming that investors are rational and risk-averse, Markowitz (1952) shows that they are better off if they invest in fully diversified portfolios (also called mean-variance-efficient portfolios), that is, portfolios which exhibit the lowest possible risk for a given level or returns or, alternatively, portfolios which yield the highest possible returns for a given level of risk. Thus, Sharpe (1964), Lintner (1965), and Mossin (1966) build on the concept of diversification to formulate independently the Capital Asset Pricing Model (CAPM). More specifically, Sharpe (1964) assumes the existence of a risk-free asset available to investors on the market in unlimited amounts, and demonstrates that diversification through the combination of the optimal portfolio and the riskless asset reduces firm-specific risk to insignificant levels and leads to a linear relationship between return and systematic risk, known as the CAPM.

Although the CAPM is appealing, it has been criticised from several perspectives, with one of the major criticisms being its inability to fully describe stock returns, with patterns left unexplained termed anomalies. As a matter of fact, Banz (1981) documents the size anomaly in average stock returns, which reflects the ability of small companies (small caps) to outperform large companies (large caps), and which is not captured by the CAPM. Similarly, Basu (1977) uncovers the value anomaly in stock returns and attributes the anomaly to the misspecification of the CAPM. The value effect designates the tendency of companies with high fundamental-to-price ratios (called value stocks) to generally outperform their low fundamental-to-price ratios counterparts (called growth stocks). Lastly, Jegadeesh and Titman

(1993) reveal the existence of the momentum anomaly in the cross-section of stock returns, which refers to the tendency of companies which have performed well in the past (past winners) to keep performing well in future while those which have experienced poor results in the past (past losers) continue to perform poorly in future.

The existence of size, value, and momentum anomalies has fuelled the debate of whether they are manifestations of risk not captured by CAPM's beta (rational view) or they are rather manifestation of security mispricing (irrational view). Proponents of the rational view such as Fama and French (1992, 1993), contend that these anomalies reflect additional risk borne by investors on capital markets and, consequently, the associated style premiums are actually compensation for risk. In this regard, they develop a three-factor model of asset pricing designed to capture the size and value effects left out by the CAPM (Fama and French, 1993). Meanwhile, Carhart (1997) proposes a four-factor model which augments the aforementioned three-factor model with a factor designed to account for the momentum effect. Conversely, advocates of the irrational view, such as DeBondt and Thaler (1985), and Lakonishok, Shleifer, and Vishny (1994), argue that the anomalies exist because of the irrational behaviour of investors. The latter view is part of a broader school of thought known as behavioural finance.

Behavioural finance studies the effect of investor psychology on financial markets and argues that because investors are subject to errors in their judgments, they often make decisions that fail to maximise their expected utility. Tversky and Kahneman (1974) provide evidence of the impact of investors' psychology on financial markets by identifying behavioural biases which lead investors to make suboptimal decisions. The prospect theory of Kahneman and Tversky (1979) further demonstrates that investors behave irrationally when they make decisions in situations of uncertainty. The irrational behaviour of these investors usually manifests in the market in the form of overreaction and underreaction. Overreaction describes a situation where investors react too sharply to new and unexpected information arriving on the market, whereas underreaction refers to a situation whereby investors react too slowly to fresh information coming to their attention. Proponents of behavioural finance, such as Lakonishok, Shleifer, and Vishny (1994) argue that investor overreaction drives the value premium on stock markets, thereby affirming that the value anomaly results from irrational behaviour.

Following the pioneering works documenting the existence of size, value, and momentum effects on capital markets, numerous studies have been carried out to investigate whether the anomalies exist out of the original samples used and are pervasive.

Subsequent to the study by Banz (1981), findings by Reinganum (1983) support the existence of the size anomaly on capital markets, as well as Fama and French (1992, 1993), and Hou and van Dijk (2018). However, findings by Fraser (1995), Horowitz, Loughran, and Savin (2000a, 2000b), and Schwert (2003), among others, argue that the size anomaly has attenuated or disappeared after it was discovered, though van Dijk (2011) asserts that claiming the demise of the anomaly is premature. Similarly, the value premium is documented on international markets by studies such as Fama and French (1992), Lakonishok, Shleifer, and Vishny (1994), and Asness, Moskowitz, and Pedersen (2013), even though few studies contend that the value anomaly has vanished or diminished to insignificant levels over time (see for example Schwert, 2003). Jegadeesh and Titman (1993, 2001) document and confirm the momentum effect on international markets, supported by other studies such as Fama and French (2012). Conversely, few studies argue that the effect has attenuated over time (for instance, Chordia, Subrahmanyam, and Tong, 2014).

A significant number of studies on the South African stock market uncover the existence of the aforementioned anomalies on the JSE, including for example van Rensburg (2001), van Rensburg and Robertson (2003a, 2003b), Basiewicz and Auret (2009), Hoffman (2012), and Page and Auret (2017, 2018). However, as observed on international markets, a few studies assert that the effects have attenuated or disappeared completely (Auret and Cline, 2011; Muller and Ward, 2013; Page, Britten, and Auret, 2013; among others).

The evidence of the presence of anomalies on capital markets around the world, coupled with the inability of the CAPM to explain these anomalies, has prompted researchers to devise alternative asset pricing models to explain the patterns generated by those anomalies in stock returns. The most popular ones include the Fama-French three-factor model, and the Carhart four-factor model. Indeed, Fama and French (1993) show that their three-factor model has a stronger explanatory power than the CAPM, while Carhart (1997) finds that his four-factor model captures the momentum effect, which is left out by the three-factor model. Subsequent to these early studies, several studies have investigated whether these multifactor models explain the style effects in markets outside the U.S., including South Africa (see for instance Basiewicz and Auret, 2010; Fama and French, 2012; Boamah; 2015). Though the bulk of the related asset pricing literature provides evidence of the suitability of the models, a handful of studies argue otherwise, leaving the debate still open, and fuelling further research pertaining to asset pricing models.

Parallel to the development of multifactor asset pricing models, studies have looked into the pervasiveness of size, value, and momentum effects, owing to the fact that evidence of their existence is not unanimous. In other words, researchers have investigated whether these style effects are cyclical in nature. For example, Krueger and Johnson (1991) and Sarwar, Mateus, and Todorovic (2017) document the cyclicality of the size effect on international markets, Gulen, Xing, and Zhang (2011) document a time-varying value premium on capital markets, while Chordia and Shivakumar (2002) provide evidence of the cyclical pattern of the momentum effect. However, few studies in this area have been undertaken on the JSE, with mixed conclusions (see for instance, Barnard and Bunting, 2015; and Hsieh, 2015).

Lastly, the everlasting debate inherent to the rationale behind the existence of size, value, and momentum effects (risk or mispricing) has drawn a lot of attention and driven many studies on international markets. For example, Fama and French (1992, 1993, and 1995) contend that the size effect occurs because of higher operating risk endured by small caps, while the value premium stems from higher distress risk embedded in value stocks. Besides, the momentum effect is attributed to macroeconomic risk by Chordia and Shivakumar (2002). Conversely, Hou and Moskowitz (2005) report that the size effect might be caused by the underreaction of investors to new and unexpected information, while Lakonishok, Shleifer, and Vishny (1994) show that the value effect emerges as a result of investor overreaction to prior positive performance of growth stocks and prior negative performance of value stocks. Finally, the momentum anomaly is viewed by Chan, Jegadeesh, and Lakonishok (1996) as a consequence of the underreaction of investors to earnings-related unexpected information. Surprisingly, the rationale of the anomalies tends to be overlooked as far as studies on the JSE are concerned.

1.2 Research Motivation

There are several motivating factors driving this study. First of all, prior research investigating the presence of size, value, and momentum effects on the JSE as well as the suitability of multifactor asset pricing models to explain these effects is relatively limited compared to studies on international markets and, more importantly, yield divergent results. Van Rensburg (2001) and van Rensburg and Robertson (2003a) find that small caps perform better than large caps on the JSE, hereby providing evidence of the size effect. This evidence is confirmed by Basiewicz and Auret (2009) as they reveal a significant size effect on the JSE over the period from 1992 to 2005. These findings are later supported by results from studies such as Strugnell, Gilbert, and Kruger (2011), Hoffman (2012), and Hsieh (2015). However, Auret and Cline (2011), Muller and Ward (2013), Hammar (2014), and Page, Britten, and Auret (2016) find no significant size premium on the JSE.

With respect to the value effect, Fraser and Page (2000) discover a significant monthly value premium of approximately 0.6% over the period 1973 – 1997 on the South African stock market. Their results are later confirmed by van Rensburg (2001), van Rensburg and Robertson (2003a), Auret and Sinclaire (2006), Basiewicz and Auret (2009), Hoffman (2012), and Muller and Ward (2013), among others. On the contrary, Auret and Cline (2011) assert that the value effect is not significant on the JSE, while Hammar (2014) and Hsieh (2015) report inconclusive findings with regard to the existence of a significant value effect on the JSE.

Fraser and Page (2000) equally document the existence of the momentum effect in South Africa, since they report a monthly and statistically significant momentum premium of 0.76% during the period 1973 – 1997. Their results are backed by subsequent studies, including van Rensburg (2001), Hoffman (2012), Hodnett, Hsieh, and van Rensburg (2012), and Page and Auret (2017, 2018), among others. Conversely, van Rensburg and Robertson (2003a) contend that the momentum effect is not present on the JSE, while Page, Britten, and Auret (2013) argue that the effect has attenuated to negligible levels over time.

Empirical findings focusing on multifactor asset pricing models on the JSE are also quite contradictory. Indeed, studies such as Basiewicz and Auret (2010), Sacco (2014), Mahlophe (2015), and Tony-Okeke (2015) claim that the three-factor model of Fama and French (1993) explains stock returns on the JSE, whereas Boamah (2015) and Karp and van Vuuren (2017) conclude otherwise. Similarly, Mahlophe (2015) and Tony-okeke (2015) reveal that Carhart four-factor model exhibits a strong explanatory power on the South African stock market. On the contrary, Boamah (2015) shows that the model should be implemented with caution on the JSE as it fails to capture size, value, and momentum effects satisfactorily.

Second, the cyclical behaviour of size, value, and momentum premiums has been given little attention in the South African literature as empirical evidence pertaining to the latter on the JSE is scarce. The study by Graham and Uliana (2001) about the presence of the value effect in South Africa over the period 1987 – 1996 reveals that growth stocks outperform value stocks during the first half of the period, but underperform them during the other half of the period, hinting at the cyclical pattern of the value premium. Years later, Hodnett (2014) and Hsieh (2015) find that the value premium tends to fluctuate throughout the business cycle on the JSE, while Barnard and Bunting (2015) report that large stocks perform better than small stocks during the 2008 global financial crisis period on the South African stock market (reversal of the size effect).

Third, the continuing debate focusing on the drivers of size, value, and momentum premiums on capital markets has not been specifically addressed in the South African literature on market anomalies, unlike on international markets where the debate has drawn a lot of attention. The two major opposing views in this regard involve the proponents of the risk-based explanation of the style premiums who affirm that the premiums emerge because investors require higher returns for additional risk embedded in small stocks, value stocks, and past winners (see for example Chan and Chen, 1991; Fama and French, 1995; and Daniel and Moskowitz; 2016). At the other end of the spectrum, proponents of the behavioural explanation contend that the style premiums result from mispricing caused by investor's underreaction and overreaction to fresh and unanticipated information brought to their attention (see for instance Lakonishok, Shleifer, and Vishny, 1994; Barberis, Shleifer, and Vishny, 1998; and Hou and Moskowitz, 2005).

These three major gaps identified in the South African literature on market anomalies and asset pricing, thus, motivate this study since they call for further studies on the subject matter.

1.3 Problem Statement and Research Objectives

The above succinct review of prior literature brings to light the following issues. Although studies pertaining to the existence of size, value, and momentum effects on the JSE largely concur with international evidence, they remain quite limited as compared to studies on international markets, and reveal more mixed conclusions. Prior research investigating the ability of multifactor asset pricing models to account for the aforementioned style effects in average stock returns is equally limited and provides rather divergent results. Studies such as Auret and Cline (2011) argue that the mixed conclusions may stem from differences in study periods.

Moreover, empirical evidence contends that style premiums are cyclical in nature. However, little research has been carried out on South African markets with respect to the cyclicality of size, value, and momentum effects. Finally, studies addressing the risk/mispricing debate with respect to size, value, and momentum premiums on the JSE have not been found at the time of writing this thesis. In this regard, a further investigation of the presence, cyclicality, and rationale of size, value, and momentum effects on the JSE should add relevant content to market anomalies and asset pricing literature and be of interest to academics and practitioners.

Consequently, the following research questions are formulated:

1. *Do size, value, and momentum anomalies exist on the JSE over the examination period? If so, do the CAPM, Fama-French three-factor model, Carhart four-factor model, and Fama-French five-factor model explain these anomalies in average stock returns?*

2. *Are size, value, and momentum effects cyclical on the JSE? If so, what is the nature of their relationship with the business cycle (procyclical or countercyclical)?*

3. *Are size, value, and momentum premiums driven by risk on the JSE? If so, are small stocks riskier than large stocks? Are value stocks riskier than growth stocks? Are winner stocks riskier than loser stocks?*

In order to answer the research questions stated above, research objectives are defined accordingly, as presented below:

1. Investigate the existence of size, value, and momentum effects on the JSE. This objective is achieved by analysing the average monthly returns on 18 portfolios formed on size and book-to-market ratio (9 portfolios) and on size and MOM12 (9 portfolios) over the whole examination period, and over the sub-periods corresponding to the phases of the South African business cycle identified in the examination period. Size here refers to the market capitalisation of firms included in the study sample. Book-to-market ratio (B/M) refers to the ratio of a company’s book value to its market

value; and MOM12 designates the prior 12-month returns yielded by a company's stock.

2. Conduct a performance attribution analysis of the 18 portfolios mentioned above, over the examination period. In other words, time-series regressions of average monthly returns on style portfolios on factors of the CAPM, Fama-French three-factor model, Carhart four-factor model, and Fama-French five-factor model are performed over the study period. This analysis is useful to establish their explanatory power and the drivers of stock returns on the JSE over the examination period.

3. Investigate the cyclical behaviour of style premiums on the JSE over the examination period. In other words, the objective here is to establish the pervasiveness of the style premiums. To this effect, performance evaluation measures are computed for each of the three style factors replicating the size, value, and momentum effects on the JSE. The performance analysis is carried out over the full study period and over the specific sub-periods outlined above.

4. If the style premiums are cyclical, determine whether they vary in tandem with (procyclical) or inversely to (countercyclical) the business cycle.

5. Investigate whether size, value, and momentum premiums are driven by risk on the JSE. This objective is achieved through the analysis of beta, obtained by performing time-series regressions of premiums generated by factor portfolios on the market risk factor. Again, the analysis is conducted for the full study period and over the sub-periods previously defined. Beta measures the sensitivity of the factor premiums to systematic risk and, therefore, sheds light on the behaviour of factor premiums in relation to variations in the magnitude of systematic risk.

6. Investigate whether small caps are riskier than large caps, value stocks riskier than growth stocks, and winner stocks riskier than loser stocks on the JSE. Performance measures of factors portfolios described above are computed compared over the phases of the South African business cycle.

Achieving the above objectives contributes to a deeper understanding of the cyclical behaviour of size, value, and momentum effects, and provides relevant insights to investors and asset managers on the performance of investment styles with respect to economic and market conditions on the South African stock market.

1.4 Research Contribution

This study's contribution to the body of knowledge is manifold. First, the study further investigates the existence of size, value, and momentum anomalies on the JSE, by extending the examination period as compared to prior studies, to include the latest data available at the time of writing, as the study period runs from 1 January 2002 to 31 December 2018. More important, the study looks at the movements in the magnitude of the style effects over the different phases of the South African business cycle, following the controversial claims that the anomalies have disappeared after they were first identified (see for example Schwert, 2003, and Auret and Cline, 2011). In this regard, this study provides possible reasons to, and attempts to reconcile, these divergent results in the context of the JSE.

In addition, the present study contributes to a better understanding of the Fama-French five-factor model (FF5F), which is relatively new and has been tested on the JSE by only a handful of studies, such as Mahlophe (2015) and Charteris, Rwishema, and Chidede (2018). Indeed, this study includes an analysis of the suitability of FF5F to explain size, value, and momentum on the JSE, as well as a comparative analysis of the explanatory power of the FF5F and the three-factor model of Fama and French (FF3F). Although Mahlophe (2015) equally addresses this issue in her study covering the period 2002 – 2014, her study carries out the comparison from a sectorial perspective. However, the current study takes a more comprehensive approach to the analysis of the relative performance of FF3F and FF5F and over a longer examination period. The results of this study should be relevant to investors and asset managers who rely on asset pricing models to estimate expected returns, since a stronger explanatory power means a better accuracy in evaluating stock or portfolio performance. Besides, through a performance attribution analysis of asset pricing models, the study sheds light on the drivers of size, value, and momentum premiums on the JSE and would, therefore, be of importance to investors who implement these investment styles.

One of the major contributions of this study is to provide a much clearer picture of the behaviour of size, value, and momentum premiums on the South African stock market, by specifically investigating their cyclical trends over an extended period of time. As mentioned earlier, few studies have examined this topic on the JSE, but have focused on one or two of the anomalies cited above, or have focused on a relatively short period of time. For example, Graham and Uliana (2001), Hodnett (2014), and Hsieh (2015) focus on the cyclicality of the value premium. Meanwhile, Barnard and Bunting (2015) investigate the size and the value effects, but only over a 7-year period (2006 – 2012). More interesting, they leave the momentum out of their analysis on the basis that it probably results from liquidity issues. Conversely, this study examines the cyclicality of size, value, and momentum premiums over a period of 17 years, which is long enough to include two business cycles (2002 - 2009 and 2009 - 2018) and, therefore, provides deeper insights into the subject matter. The results would enable investors to be more mindful of the investment styles that exhibit the strongest performance depending on the phase of the business cycle the South African economy is going through at a given point in time, and adapt their investment strategies accordingly. For instance, Kwag and Lee (2006) show that the value strategy shows its strongest performance during periods of recession on the U.S. stock market, while Peltomaki and Äijö (2015) suggest the momentum investment style as a backup strategy during periods of financial crisis.

Lastly, this study investigates the risk-based explanation of size, value, and momentum premiums on the JSE, which, at the time of writing and to the author's best knowledge, has not been addressed in prior South African literature. In this regard, this study adds valuable content to the academic literature on market anomalies on the JSE. Moreover, it is of interest to investors who believe in market efficiency and are, therefore, willing to take additional risk only if they expect to earn higher premiums on their investments on the JSE.

1.5 Organisation of the Study

The present study investigates the cyclical behaviour of size, value, and momentum effects on the JSE over the period from 1 January 2002 to 31 December 2018.

In this regard, Chapter 2 presents the theoretical underpinnings of the study. More specifically, the chapter starts with an overview of the random walk theory, EMH, and MPT as these theories lay the foundations for asset pricing models developed subsequently. The chapter then discusses the origins and implications of the asset pricing models, focusing on the CAPM and the APT, before looking into market anomalies, so called because they are not explained by the CAPM. As mentioned before, the chapter focuses on the size, value, and momentum anomalies, and highlights possible explanations for the existence of these anomalies on capital markets. The chapter concludes with an overview of behavioural finance, including a succinct discussion of prospect theory and behavioural biases most commonly observed on capital markets, namely overreaction and underreaction.

Chapter 3 revisits prior literature related to the issues investigated in this study. Indeed, empirical evidence pertaining to the presence of the market anomalies under investigation both on international markets and in South Africa is reviewed, including the asset pricing models that have been designed over the years to capture these anomalies. Furthermore, the chapter delves into prior research documenting the cyclical behaviour of size, value, and momentum on capital markets, and concludes with a review of the ongoing debate on the rationale of the premiums generated by those investment styles.

Chapter 4 displays the sources and types of data used, explains the process of collecting data and the rationale behind the choice of the study period. The chapter equally presents the methodology adopted to analyse the data and interpret the results, with regard to the research objectives. The chapter uses a combination of time-series regression, performance evaluation and performance attribution tools to process the data and analyse the results obtained. Finally, Chapter 4 closes with a discussion of the biases likely to influence the study, including the steps taken to mitigate the effects of these biases on the accuracy of the results obtained.

Chapter 5 presents the results inherent to the presence of size, value, and momentum anomalies on the JSE over the examination period. The analysis is broken down following the phases of the South African business cycle identified in the examination period. The analysis of the results from the time-series regressions performed using the CAPM and style-based multifactor asset pricing models (Fama-French three-factor model, Carhart four-factor model, and Fama-French five-factor model) is equally carried out, including an analysis of the drivers of the anomalies (performance attribution).

Chapter 6 presents and discusses the results pertaining to whether size, value, and momentum premiums exhibit a cyclical pattern on the JSE, as the previous chapter reveals that the magnitude of these effects tends to fluctuate over time. The analysis makes use of risk-unadjusted and risk-adjusted performance evaluation tools, and breaks down the examination periods into sub-periods in the same procedure as carried out in Chapter 5. The chapter concludes with a discussion about the trends followed by the movements in the style premiums in comparison to the trend in the business cycle.

Chapter 7 engages the debate regarding the rationale behind the existence of size, value, and momentum anomalies, and approaches it from a risk-based perspective. Using market beta, which proxies for systematic risk, as the measure of risk, the chapter examines the exposure of the style premiums to market risk over the various phases of the South African business cycle embedded in the examination period. Besides, the chapter investigates the risk relationship between stocks found at the extreme points of each effect's spectrum (small versus big, value versus growth, winners versus losers).

Chapter 8 summarises the study and highlights the limitations of the latter as well as possible avenues for future studies in the area of interest.

CHAPTER 2 – THEORETICAL OVERVIEW

2.1 Introduction

The development of asset pricing theories has originally been guided by the concept of risk and return, and the assumption of investors' rationality. Underpinning theories of asset pricing posit that on the one hand, investors are not only sensitive to returns they expect from their investments, but also to the risk embedded in the latter. Consequently, they are willing to take on more risk if they are rewarded with extra return commensurate to the additional risk taken. On the other hand, investors are rational and engage in capital market transactions after a well-thought and informed decision-making process. This is commonly known as the traditional view of finance.

However, psychologists over the past forty years have challenged the traditional view of investor behaviour as they operate on financial markets. Psychologists argue that investors are not always rational; they are driven by emotions and they are prone to cognitive errors in making investment decisions. As a result, they do not always make optimal decisions. This psychologist approach to investors' decision-making process is commonly known as behavioural finance. Behavioural finance has gained momentum over the years, especially due to the observation of asset pricing phenomena inconsistent with the traditional view, and which the latter has not convincingly explained.

This chapter discusses the underpinning theories of asset pricing models, starting with the Random Walk Theory and the Efficient Market Hypothesis, before delving into the Modern Portfolio Theory, the Capital Asset Pricing Model, and the Arbitrage Pricing Theory. The chapter then proceeds with a review of well-known anomalies that have been observed in financial markets, along with the most popular reasons that have been put forth to explain those anomalies. The chapter closes with the behavioural view of asset pricing and presents the major theories and biases that challenge the underlying assumptions of asset pricing theories.

2.2 Random Walk Theory

The random walk theory asserts that stock prices move in an irregular and uncertain fashion. In other words, they follow a random walk. This randomness of prices implies that it is impossible to predict future stock prices from past data. The origins of the random walk theory date as far back as 1860s and are attributed to Jules Regnault. In his 1863 book titled "Calcul des Chances et Philosophie de la Bourse", Regnault examines the behaviour of stock prices on the French stock market in an attempt to design a model that can be used for short-term speculation. Regnault claims that stock prices reflect all the information inherent to a stock at any point in time and vary only when new and unexpected information arrives on the market. Furthermore, he claims that variations in stock prices are independent and, therefore, movements in previous prices are useless in predicting future stock price movements. By formulating these two assumptions, Regnault lays down the foundations of the random walk theory (and of the Efficient Market Hypothesis). The random behaviour of stock price variations is later tested by Bachelier. Using a mathematical approach, Bachelier (1900) finds that fluctuations in current prices are uncorrelated to previous ones, thereby providing evidence of the random walk theory.

Though the concept of random walk originated in the 1860s, the theory is officially introduced by Maurice Kendall. Kendall (1953) studies the weekly change in prices of 19 British industrial stock price indices, along with change in prices of wheat in Chicago and cotton in New York. He finds that the correlation between price changes from one week to the other is weak and practically negligible. In other words, the variation in asset prices is random. Irrespective of past performance, prices are as likely to move upward as they are to move downward, thereby providing no trend that can be exploited to forecast future price movements.

According to Malkiel (1999), the random walk of asset prices should not be viewed as a sign of irrational behaviour on the part of financial market participants. Rather, the unpredictability of asset prices reflects market efficiency as analysts constantly adjust their price estimations to the arrival of new and unexpected information on the market. Although the market might get too optimistic from time to time, prices eventually get corrected once the market acknowledges the fundamental value of assets. The random walk theory therefore paves the way for the formulation of the Efficient Market Hypothesis (EMH).

2.3 Efficient Market Hypothesis (EMH)

Fama (1965) studies the behaviour of stock prices on capital markets with the purpose of providing further evidence of the random walk of stock prices. More specifically, he tests the two underlying assumptions of the random walk theory, namely the independence of successive changes in stock prices, and the conformity to some probability distribution with regard to these changes in prices. The author finds that although significant changes in prices are likely to trigger subsequent significant changes in either direction, this correlation is insignificant and, overall, the conclusions of the study are consistent with the random walk behaviour of stock prices.

Fama (1970) uses the random walk theory as a stepping stone to formulate the Efficient Market Hypothesis (EMH), which states that prices of securities fully reflect all information available concerning those securities, at all times. He asserts that the phrase “fully reflect” implies the non-correlation and probability distribution of successive changes in the price of stocks, which are the two underlying hypotheses of the random walk theory. Moreover, he states that the EMH equally builds on the concept of market equilibrium. This means that in efficient markets, investors can only earn returns commensurate to the risk embedded in the security they invested in. It also means that market efficiency should be tested using a relevant market equilibrium model. This implication later gives rise to the Joint Hypothesis problem.

Fama (1970) distinguishes between three forms of market efficiency, depending on the kind of information available on the market and reflected in security prices: the weak form, the semi-strong form and the strong form of market efficiency.

The weak form of market efficiency contends that current security prices already reflect all information available on the market that can be obtained through the analysis of past data, such as historical prices and rates of return. This hypothesis holds that there is no correlation between historical data and future prices or rates of return. In other words, security prices move randomly and analysing past data in order to predict future prices is worthless. Thus, Fama (1970) posits that tests of the weak form of EMH have been actually geared towards uncovering evidence for or against the random walk theory, and most of the evidence shows that future stock prices cannot actually be predicted based on past prices (see for example Kendall, 1953).

The semi-strong form of market efficiency advocates that all publicly available information about securities in the market is already impounded in their current prices. It means that security prices quickly adjust to the infusion of any new public information in the market. Thus, Fama (1970) affirms that tests of the semi-strong form of EMH actually investigate how fast security prices incorporate and reflect new information. The latter mainly include announcements of stock splits, earnings, and seasoned equity offerings, among others.

Finally, the strong form of market efficiency posits that all information available about securities, past and present, public and private, is incorporated in their current prices. In other words, there is no information monopoly by a given group of market participants with regard to securities traded on the market. Fama (1970) acknowledges that this form of market efficiency is quite extreme and may not exactly hold in practice, since corporate managers would be expected to have access to information about their company not yet available to the public, which they can act upon to outperform the market.

In his 1991 follow-up paper, Fama (1991) renames the tests pertaining to the various forms of EMH and broadens the scope of the weak form tests to accommodate the latest developments in the area of market efficiency. More specifically, the weak form tests are referred to as tests for return predictability, and now encompass tests on the validity of asset pricing models (especially the Capital Asset Pricing Model - CAPM) with respect to market anomalies which have been recently brought to light (size, value, and January anomalies). Besides, the semi-strong form tests are referred to as event studies while the strong form tests are renamed tests for private information. According to Fama (1991), the most striking issue pertaining to the EMH remains the Joint Hypothesis problem. Indeed, with reference to his 1970 work, he contends that the EMH cannot be tested in isolation, but through the use of an asset pricing model. Consequently, when tests of market efficiency reveal anomalous patterns in stock returns (patterns not predicted by the CAPM), it is difficult to determine whether those anomalous patterns result from market inefficiency, or from flaws in the model used, or from both. Nevertheless, research on market efficiency and asset pricing models remain highly relevant to academics and practitioners as it helps to better understand the behaviour of asset returns and enables professionals to improve investment practices (Fama, 1991).

The foundations of asset pricing models, which have been developed to estimate expected returns on securities, lie in the Modern Portfolio Theory (MPT).

2.4 Modern Portfolio Theory (MPT)

Modern Portfolio Theory (MPT) was developed by Harry Markowitz in his 1952 book titled "Portfolio Selection". MPT is based on the idea that investors are better off if they invest in a wide range of assets than in a single type, as they will have to bear less risk. Through MPT, Markowitz (1952) defines a framework investors should use to construct their portfolios of assets in such a way to maximise expected returns for a given level of risk, or to minimise risk for a given level of returns.

Markowitz (1952) argues that when investors pick stocks to construct their portfolio, they should not evaluate their risk and return in isolation, but in relation to how they vary with respect to each other. He formalises the concept of diversification and asserts that a well-diversified portfolio (whose stocks are not perfectly positively correlated) exhibits a lower risk than the sum of the risks borne by individual assets included in the portfolio. This is due to the fact that efficient diversification reduces the covariance among stocks in the portfolio.

Markowitz (1952) posits that the mean of the probability distribution of expected returns of an asset is a suitable proxy for its expected return, while the variance of the returns is a suitable proxy for its risk. The algebraic representation of the expected return and the variance of a portfolio of securities are given by Markowitz (1952) as follows:

Expected return E: $E = \sum_{i=1}^{N} X_i \, \mu_i$ (2.1)

Variance V: $V = \sum_{i=1}^{N} \sum_{j=1}^{N} \sigma_{ij} \, X_i X_j$ (2.2)

where:

X_i, X_j represent the proportion of the investor's wealth allocated to security i and security j respectively ($\sum X_i = 1$ and $\sum X_j = 1$)

μ_i is the expected value of the return on security i

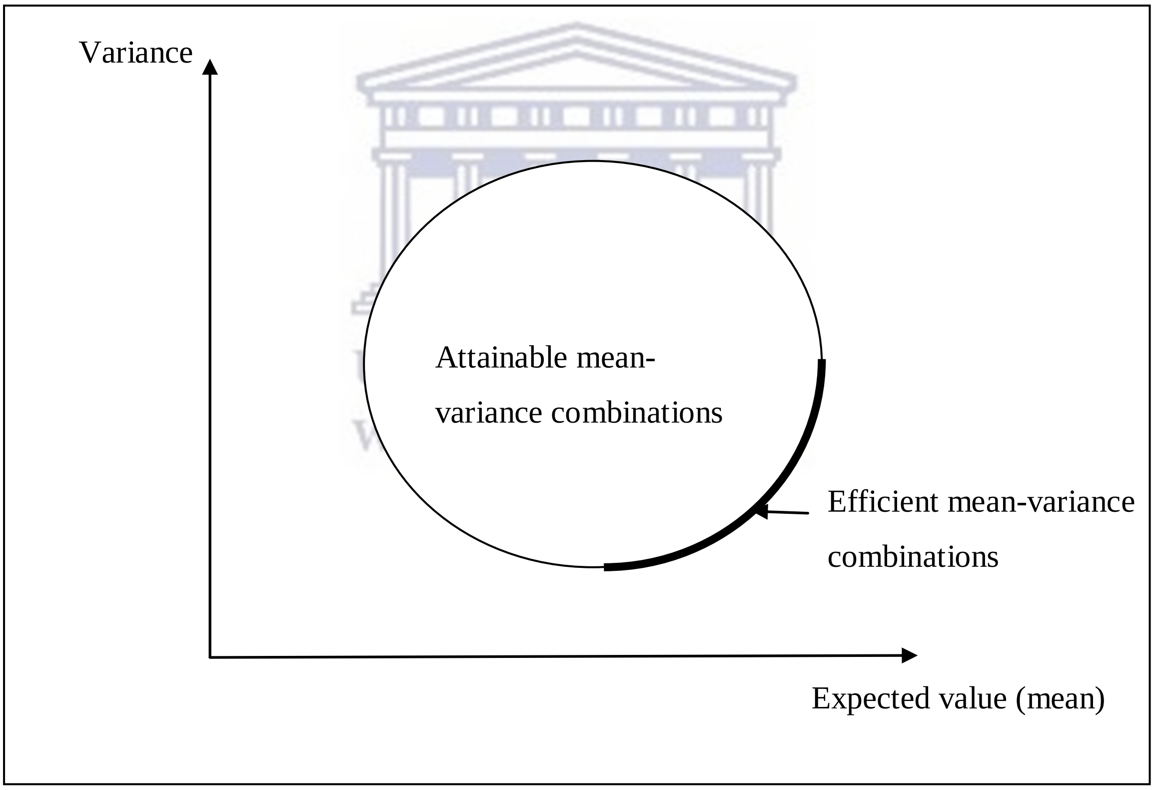
σ_{ij} is the covariance between the return on security i and the return on security j

N is the number of securities in the portfolio (finite)

According to Markowitz (1952), several mean-variance combinations are available to and achievable by investors, depending on their portfolio selection. More important, as a rational being, they would be prone to select the portfolios that exhibit minimum risk for a given level of expected return or, alternatively, that provide the highest expected return for a given risk level. In other words, investors would go for portfolios which are mean-variance efficient.

Figure 2.1 shows the universe of achievable mean-variance combinations, along with the efficient mean-variance combination, represented by the dark thick segment of the figure. The set of portfolios constructed from the efficient mean-variance combinations and lying on the dark thick segment forms the efficient portfolio set or efficient frontier, and represents the best combinations of risky assets in terms of risk-return profile.

Figure 2.1: Mean-Variance Combinations



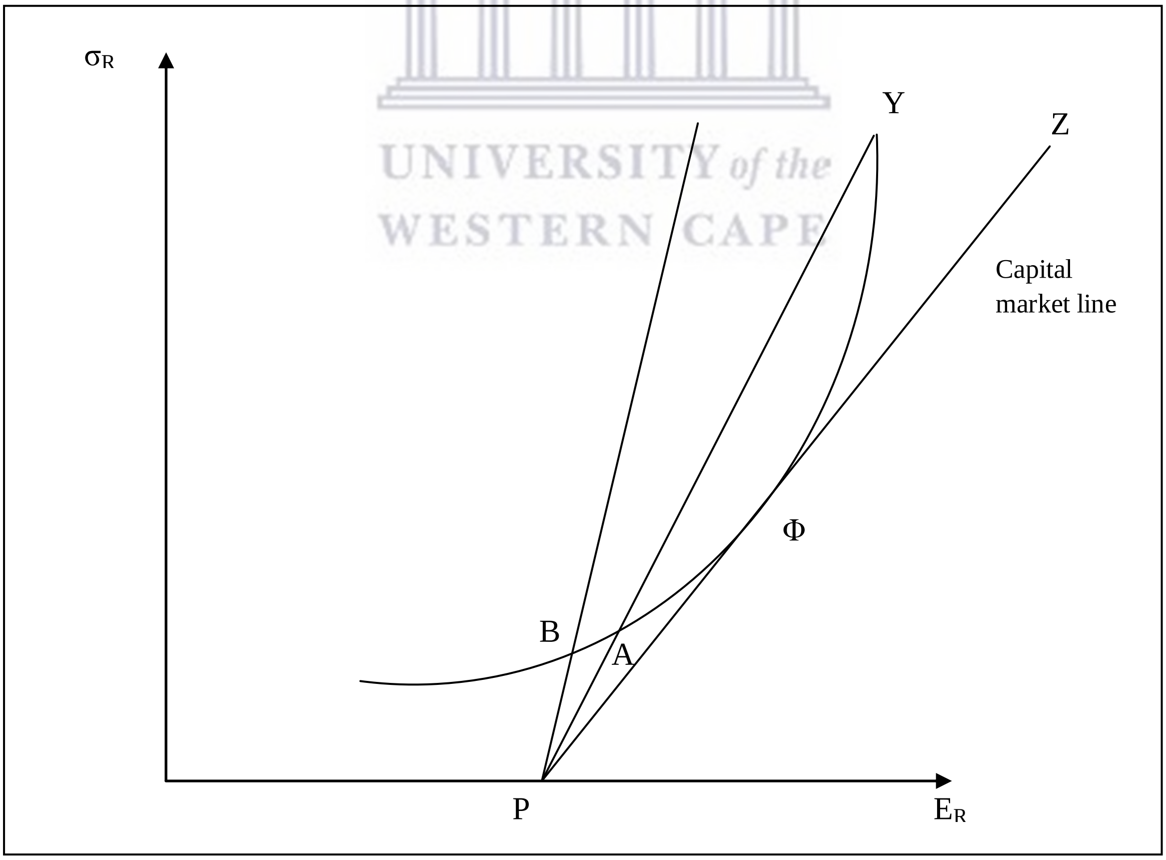
Source: adapted from Markowitz (1952)

Building on the concept of diversification and the assumption of the existence of a risk-free security available to investors on the market, Sharpe (1964) shows that the optimal portfolio can be obtained by a combination of risky assets and the risk-free security. This idea leads to the concept of capital market line and to the formulation of the well-known Capital Asset Pricing Model (CAPM).

2.5 Capital Asset Pricing Model (CAPM)

Sharpe (1964) argues that investors are faced with two types of prices on the market, a price related to time and a price related to risk. The former refers to the risk-free rate of return while the latter represents the risk premium available to investors for taking additional risk. Any combination of the risk-free security (say P) and a risky asset (say A) should result in a portfolio lying on a straight line which passes through the two elements, as depicted in Figure 2.2. More importantly, when the market is in equilibrium, investors have at their disposal a portfolio of risky assets (say Φ) found on the efficient frontier which, when combined with the risk-free security, results in a straight line tangent to the efficient frontier, and known as the capital market line (CML). Φ is the optimal portfolio of risky assets, since the CML has the steepest slope compared to all other straight lines, and, consequently, the highest Sharpe ratio. This means that Portfolio Φ, also known as the market portfolio, generates the highest risk-adjusted return from all the risk-return combinations.

Figure 2.2: Capital Market Line and Optimal Portfolio



Source: adapted from Sharpe (1964)

Sharpe (1964) assumes that investors can borrow and lend unlimited amount of money at the risk-free rate in order to achieve their portfolio selection objective. Investors with high aversion to risk will invest (buy) part of their money in the risk-free asset and the balance in the market portfolio, while those with lower aversion to risk will sell short the risk-free asset (borrow money at the risk-free rate) and add the money to their investment in the market portfolio. In either case, the various combinations will be dominated by any combination lying on the CML. In other words, Sharpe (1964) demonstrates that with the introduction of the risk-free rate, the relationship between risk and return becomes linear for efficient portfolios when the market is in equilibrium. More specifically, the linear relationship is established between portfolios' return and systematic risk, since the diversification process has reduced the unsystematic risk to a negligible level.

Sharpe (1964) further establishes that the linear relationship equally exists between the expected return and the systematic risk of individual assets. This relationship is graphically represented by the security market line (SML), as depicted in Figure 2.3.

The slope of the SML, which represents the risk premium earned by the investor for investing in an asset riskier than the risk-free asset, can be expressed from Figure 2.3 as below:

$\frac{E_{Ri} - P}{B_i g}$, which is equivalent to $\frac{E_{Rg} - P}{1}$

Equating these 2 algebraic expressions of the slope and solving for the expected return on asset i (E_{Ri}) lead to the formula of the CAPM:

$$E_{Ri} = P + B_{ig}(E_{Rg} - P) \qquad (2.3)$$

where:

E_{Ri} is the expected return on asset i

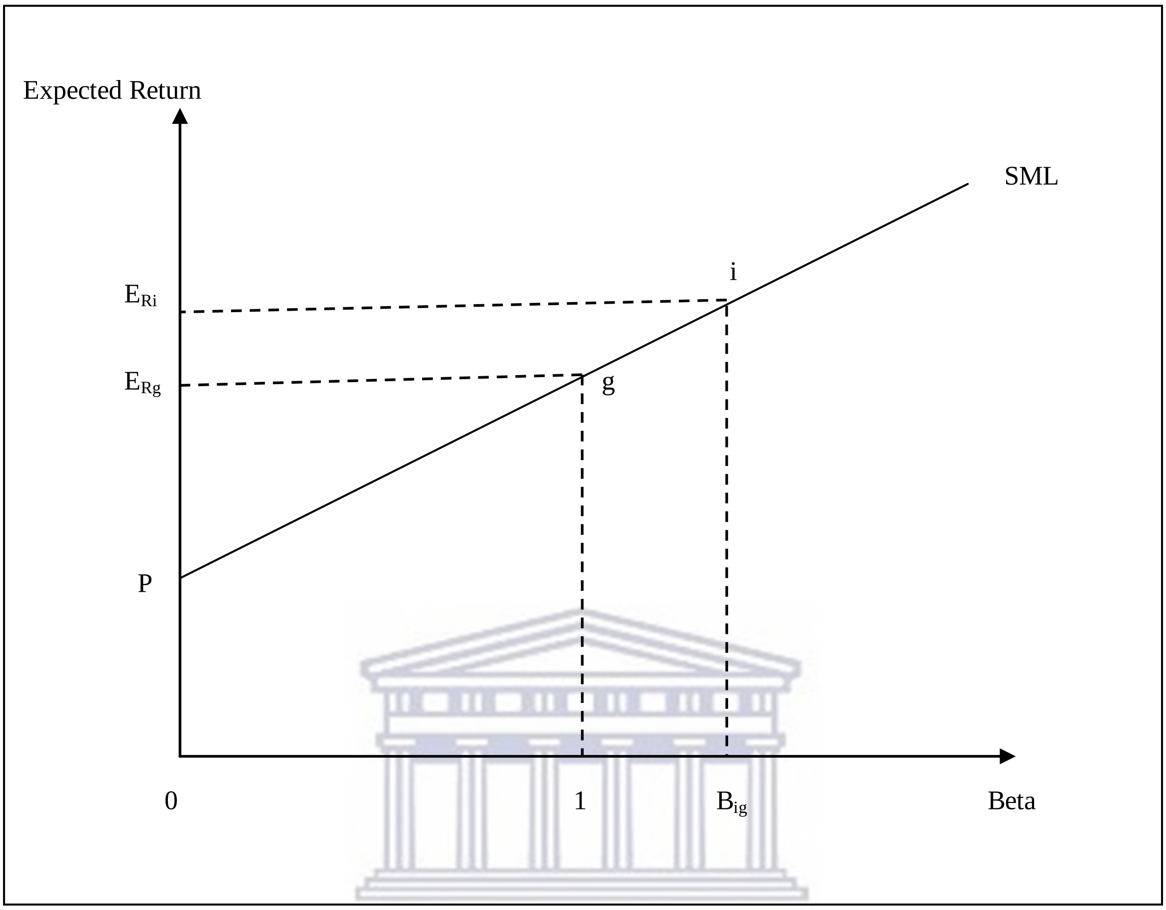
P is the risk-free rate

B_{ig} is the systematic risk of asset i

E_{Rg} is the expected return on the efficient portfolio g

$E_{Rg} - P$ is the market risk premium

Figure 2.3: Security Market Line



Source: adapted from Sharpe (1964)

Lintner (1965) and Mossin (1966) equally build on the principles of diversification and market equilibrium to derive (independently) the CAPM theory.

Though CAPM's theorisation of the estimation of expected return on an asset is very appealing, it has faced a lot of criticisms, mostly questioning how practical its assumptions are, as they are deemed too simplistic.

Absence of transaction costs, of taxation, perfect divisibility and liquidity of all traded assets, are assumptions that simply do not apply in real markets.

The CAPM assumes that investors can borrow and lend unlimited amounts at the risk-free rate. In practice, lending and borrowing rates are different from each other. Black (1972) builds on this shortcoming of the traditional CAPM to design another version of the model, which is free from riskless lending or borrowing, but which allows for unrestricted short selling of risky assets. However, unrestricted short selling of risky assets is equally an unrealistic assumption. Indeed, shorting an asset comes with uncapped liability for the investors as the price of the asset may increase without any limit. Thus, investors may have to provide collaterals for significant short selling and may not be able to invest in other risky assets with the proceeds. Besides, the volume of short sale might be limited by regulations or by the volume of assets available on the market for sale.

Roll (1977) claims that the market portfolio, as defined in the CAPM, cannot be observed. The theory does not specify the nature of assets which the market portfolio should be comprised of (stocks, bonds, commodities, real estate, human capital, among others). Besides, it is practically impossible to observe a market portfolio which encompasses all investors' assets. Consequently, common stock indices are usually considered to be suitable proxies for the market portfolio. This means that any test of the CAPM investigates whether the proxy used, and not the true market portfolio, plots on the efficient frontier. Roll concludes that empirical tests of the CAPM may not be feasible.

According to the CAPM, investors are interested in a single-period investment horizon. In practice, investors are most likely to invest over multiple periods. The single-period assumption has been relaxed to develop alternative versions of the CAPM (for example, Merton, 1973; Lucas, 1978; Breeden, 1979). According to the model, beta is sufficient to explain the expected returns on an asset. However, several studies have found that the relationship between expected return and beta is flatter than expected, showing that beta does not fully explain expected returns (Jensen, Black, and Scholes, 1972; Fama and MacBeth, 1973; among others). Furthermore, researchers have uncovered trends in expected returns that are not captured by beta, such as the size effect, the value effect, and the momentum effect (for instance Basu, 1977; Banz, 1981; and Jegadeesh and Titman, 1993).

The assumptions about investors' rationality, utility maximisation, and mean-variance efficiency have equally been challenged on the ground that investors do not always act rationally and are sometimes driven by emotions and cognitive biases (see for example Kahneman and Tversky, 1979).

The restrictive assumptions of the CAPM, coupled with its inherent flaws, motivated researchers to consider alternative asset pricing models. This search for a more realistic model led to the formulation of the Arbitrage Pricing Theory (APT).

2.6 Arbitrage Pricing Theory (APT)

Ross (1976) builds his Arbitrage Pricing Theory (APT) as an alternative asset pricing model to the CAPM following criticisms on 2 main assumptions of the latter, namely the investor's quadratic utility function (risk aversion) and the normal distribution of returns (mean-variance efficiency). More specifically, Ross (1973) argues that in the absence of a risk-free asset, investors can form a riskless portfolio (zero-beta portfolio) through arbitrage of assets which are not correlated with the market portfolio. This procedure therefore relaxes the CAPM assumption which requires the existence of a risk-free asset on the market for the model to hold. Furthermore, the author posits that investors hold different portfolios with regard to their risk-return preferences and the types of assets they favour. Thus, there is not a single market portfolio held by all investors. This relaxes the market portfolio condition of the CAPM which renders the latter non-testable.

Finally, the author shows that thanks to the law of large numbers which allows efficient diversification, unsystematic risk is reduced to negligible levels and the only risk left is the systematic risk. Systematic risk is related to common factors that affect the market as a whole, and not assets individually. In other words, systematic risk is no more proxied by the sole market risk factor as in the CAPM, but by multiple risk factors which are related to the various macroeconomic variables to which assets are exposed in the market.

Ross (1976) designs the APT model with k risk factors as follows:

$$E_i - \rho = \beta_{i1}(E^1 - \rho) + \dots + \beta_{ik}(E^k - \rho) \qquad (2.4)$$

where

E_i	is the expected return on asset i
ρ	is the return on all zero-beta portfolios
β_{ik}	is the beta coefficient for the kth risk factor
E^k	is the return on the kth risk factor
$E^k - \rho$	is the kth factor risk premium

Ross (1976) does not specify the risk factors that should be used, nor does he specify the number of factors to be considered. In order to address these issues, Roll and Ross (1980) carry out a study designed to determine on the one hand whether the risk factors describing stock returns as propounded by the APT actually exist, and on the other hand if these risk factors have associated risk premiums. Using U.S. data over the period 1962 – 1972, the study reveals that risk factors capturing movements in stock returns do exist in the U.S. over the examination period, and they need to be as many as four to accurately explain those returns. Interestingly, Roll and Ross (1980) state that market anomalies need to be revisited in the context of a multifactor model like the APT. However, the study does not dwell on the nature of the risk factors, although the authors suggest that they are likely to be related to macroeconomic forces like the interest rate.

Chen, Roll, and Ross (1986) shed light on the possible macroeconomic variables that can be considered as risk factors in the APT model. More specifically, they investigate whether unexpected fluctuations in a set of identified macroeconomic variables constitute priced risk factors explaining stock returns on the U.S. stock market, over the period from 1953 to 1984. The authors argue that since stock prices (and consequently returns) can be expressed as a function of the present value of expected dividends, macroeconomic forces that impact stock returns are the ones responsible for changes in discount rates and expected cash flows. Following this rationale, the authors identify the term spread, the risk-free rate, the risk premium, and real consumption, as relevant macroeconomic factors that influence the discount rate. Similarly, they point out expected inflation rate and expected real production level as relevant candidates influencing cash flows.

Results reveal that while the term spread, movements in risk premium, and changes in industrial production level significantly influence stock returns, the impact of fluctuations in the inflation rate on returns is quite weak. Conversely, changes in real consumption do not capture movements in stock returns. The study concludes that although the list of macro variables used is probably non-exhaustive, the variables do a good job as priced risk factors explaining stock returns and should be considered as such in the framework of asset pricing models.

In conclusion, the APT relaxes some of the most restrictive assumptions of the CAPM, such as the presence of a riskless asset, the mean-variance condition, and the reliance on a sole source of non-diversifiable risk. Thus, Ross (1976) asserts that it is more realistic and proposes the model as a relevant alternative to the CAPM, whose validity is known to have been plagued by the presence of market anomalies it is unable to explain.

2.7 Capital Market Anomalies

According to Schwert (2003), anomalies refer to results from empirical studies that violate asset pricing theories. Indeed, a significant body of literature has shown evidence of deviations from equilibrium, as defined by the CAPM, which result in abnormal returns not captured by CAPM's beta. Some of the most common anomalies include the size effect, the value effect, and the momentum effect.

2.7.1 Size Effect

The size effect refers to the negative relationship between company size (in terms of market capitalisation) and returns. More specifically, small-size companies (small caps) have been found to perform better than large-size companies (large caps) on a risk-adjusted basis.

Banz (1981) studies common stock returns on the U.S. market for the period from 1926 to 1975 and finds that shares of small companies yield a monthly and statistically significant 1.5% higher risk-adjusted returns than shares of much larger companies, on average, over the period 1936 - 1975. The persistence of the size effect over the study period leads the author to the conclusion that the presence of the anomaly is more likely to reflect CAPM misspecification than market inefficiency. Reinganum (1981) conducts a similar study, where he tests for size and value effects (the value anomaly is discussed subsequently) on the U.S. stock market over the period from 1975 to 1977. His findings support the study by Banz cited earlier since they reveal that small caps perform better than large caps by roughly 1.6% per month over the study period. The author equally concludes from the persistence of the size effect that it is more likely due to misspecification of the CAPM, rather than to market inefficiency. Subsequent studies such as Fama and French (1992, 1993), and more recently, Asness, Frazzini, Israel, Moskowitz, and Pedersen (2018), equally document a significant size effect in the U.S.

Studies carried out outside the U.S. market support the existence of the size effect. Indeed, Annaert, Crombez, Spinel, and Van Holle (2002), Schmidt, von Arx, Schrimpf, Wagner, and Ziegler (2017), and Asness et al. (2018) provide evidence for the size anomaly on European markets, while Rouwenhorst (1999) uncover similar findings on emerging markets. Lastly, several studies such as van Rensburg (2001), Basiewicz and Auret (2009), and Hsieh (2015) report that the size anomaly is prevalent on the South African stock market.

2.7.2 Value Effect

The value effect refers to the phenomenon whereby stocks with high fundamental-to-price ratios (called value stocks) yield, on average, higher risk-adjusted returns than stocks with low fundamental-to-price ratios (called growth stocks or glamour stocks).

Basu (1977) investigates the relation between stocks average returns and their corresponding price-earnings (P/E) ratios and discovers that shares that exhibit low P/E ratios (value stocks) generate higher average returns than shares that exhibit high P/E ratios (growth stocks). Basu (1983) confirms the existence of the value effect on the U.S. stock market by analysing the returns on stocks with low earnings-price (E/P) ratio and those with high E/P ratio. Actually, he shows that highest E/P portfolios earn on average 0.66% more than lowest E/P portfolios, even after controlling for the size effect. Fama and French (1992) provide further evidence of the existence of the value effect, proxied by the book-to-market (B/M) ratio. They find that the top 10% B/M portfolios outperform the bottom 10% B/M portfolios by approximately 6% per annum on average. Other studies corroborate the existence of the value effect in the U.S. (for example, Lakonishok, Shleifer, and Vishny, 1994; Fama and French, 1998, 2012; and Asness, Moskowitz, and Pedersen 2013).

Fama and French (1998) uncover a strong value premium on European, Australian, and emerging markets, confirmed by Rouwenhorst (1999) on emerging markets, as well as Annaert et al. (2002), Asness et al. (2013), and Desban and Jajir (2016) on European markets. Besides, the value anomaly is documented on the JSE by Fraser and Page (2000), van Rensburg (2001), Basiewicz and Auret (2009), and Page and Auret (2018), to name but a few. However, the conclusions about the appropriate measure of the value effect on the JSE remain mixed.

2.7.3 Momentum Effect

The momentum effect denotes a positive relationship between prior and subsequent stock prices, and refers to a situation where past underperforming stocks (losers) continue to underperform the market, while past outperforming stocks (winners) keep outperforming the market. The momentum anomaly was first documented by Jegadeesh and Titman (1993).

Jegadeesh and Titman (1993) show that there is a momentum anomaly on the U.S. stock market, in a study covering the period from 1965 to 1989. They find that buying shares that outperformed the market in the last 3 to 12 months (winners) while selling short shares that underperformed the market over the same period (losers), yield positive abnormal returns over the next 12 months post formation. In a follow-up paper, Jegadeesh and Titman (2001) investigate the presence of the momentum effect in the U.S., using an extended examination period (1965 – 1998) as compared to the one in their 1993 paper. Following the same methodology as in Jegadeesh and Titman (1993), they show that a momentum trading strategy yields a monthly return close to 1.4% over the study period. Similar studies support these findings on the U.S. market, including for instance Fama and French (2012), Asness et al. (2013), and Zaremba (2018).

The momentum anomaly is documented in Europe by Rouwenhorst (1998) who demonstrates that loser portfolios underperform their winner counterparts in 12 European countries. These results are supported by Fama and French (2012) in 16 European markets. Rouwenhorst (1999) equally documents the momentum effect on emerging markets, and his findings are backed by Cakici, Fabozzi, and Tan (2013), and Zaremba (2018), among others. In the South African context, Fraser and Page (2000) find that the average monthly winner – loser spread over the period 1973 – 1997 amounts to 0.76% and is extremely statistically significant. Van Rensburg (2001), Hoffman (2012), and Page and Auret (2018) report strong momentum profits on the JSE.

2.7.4 Possible Explanations of Market Anomalies

Explanations that have been proposed to explain market anomalies fall under two broad categories, depending on whether the anomalies are perceived from a rational or an irrational perspective.

2.7.4.1 Rational Explanations

Proponents of a rational explanation to anomalies argue that these anomalies arise because of the risk faced by investors when they trade stocks on the market. Investors face several risks when investing in securities, and they require premiums for any additional risk taken.

Fama and French (1993) provide an appealing risk-based explanation of the size effect and the value effect. The authors advocate that the size effect is inherent to the earnings capacity of companies in the sense that when the value effect is controlled for, small caps exhibit lower profits than large caps. Put another way, small-size firms are riskier because they tend to generate lower profit than large-size companies. In addition, their earnings are more volatile. Consequently, investors require a premium to compensate them for investing in riskier stocks. Fama and French (1993) construct a risk factor which represents the higher returns earned by small caps over large caps, known as the small minus big (SMB) factor.

From the risk-based point of view, the value effect is perceived as a premium required by investors to compensate them for venturing in value stocks, considered riskier than growth stocks. Value stocks are companies with poor earnings prospects. In other words, they are distressed stocks which investors are willing to invest in provided they are rewarded with higher returns. Conversely, growth stocks enjoy strong earnings prospects. Investors consider this type of stocks less risky and require a relatively low rate of return for them. As a result, value stocks tend to outperform growth stocks (Fama and French, 1993). In their three-factor model of asset pricing, Fama and French (1993) design a risk factor which captures the value effect in average stock returns, termed high minus low (HML).

The Fama-French three-factor model times-series regression equation is given by

$$R(t) - RF(t) = a + b[RM(t) - RF(t)] + sSMB(t) + hHML(t) + e(t) \qquad (2.5)$$

where

R	is the return on the portfolio of common stocks
RF	is the one-month Treasury bill rate
a	is the intercept of the regression
RM	is the return on the market portfolio
SMB	is the portfolio designed to replicate the size factor
$RM - RF$	is the excess market return
HML	is the portfolio designed to replicate the value factor
b, s, h	are factor loadings on the market, size, and value factors
e	is the regression residual

According to Fama and French (1993), the factor loadings on market, size, and value risk factors explain all of the variations identified in expected return. Therefore, alpha should not be different from zero.

Fama and French (1996) find that the three-factor model is unable to capture the momentum effect of Jegadeesh and Titman (1993). Carhart (1997) thus extends the three-factor model with a fourth factor designed to capture the momentum effect.

The Carhart four-factor model times-series regression equation is given by

$$r_{it} = \alpha_{iT} + b_{iT}RMRF_t + s_{iT}SMB_t + h_{iT}HML_t + p_{iT}PR1YR_t + e_{it} \qquad (2.6)$$

where

r_{it}	is the return differential between the return on a portfolio of common stocks and the yield on the 1-month Treasury bill
$RMRF$	is the excess return on a market proxy
α	is the intercept of the regression
SMB	is the return on a value-weighted portfolio designed to replicate the size factor
HML	is the return on a value-weighted portfolio designed to replicate the book-to-market factor
$PR1YR$	is the return on a value-weighted portfolio designed to replicate the 1-year momentum factor in stock returns
b, s, h, p	are factor loadings on the market, size, value, and momentum factors
e	is the regression residual

Interestingly, Carhart (1997) describes his four-factor model as model designed for performance attribution analysis, and does not address the issue of whether the momentum factor has a risk-based rationale. Nonetheless, some researchers have delved into the issue and provided evidence that the momentum premium might be compensation for risk. For example, Chordia and Shivakumar (2002) link momentum profits to macroeconomic risk, while

Peltomäki and Äijö (2015), and Ruenzi and Weigert (2018) attribute the momentum effect to voltatility risk and crash risk respectively. Notwithstanding, the existence and persistence of the momentum anomaly have mostly been attributed to the irrational behaviour of the market.

2.7.4.2 Behavioural Explanations

The behavioural perspective claims that market anomalies emerge because investors do not always act rationally. Due to emotions such as fear, and cognitive biases such as overconfidence, investors tend to exhibit erratic behaviour which makes stock prices deviate from equilibrium, hence causing anomalies observed in capital markets. In other words, the market is inefficient. The behavioural rationale of market anomalies has been extensively documented under the school of thought known as behavioural finance.

2.8 Behavioural Finance

Behavioural finance examines how the psychology of investors affects their behaviour in financial markets. Behavioural finance argues that investors, just like any other human being, are subject to emotions, judgment errors, and subjective thinking. Consequently, they are likely to behave irrationally and act in a way that does not maximise their expected utility. Behavioural finance challenges the expected utility theory (EUT), which is one of the key underlying theories of market efficiency.

The expected utility theory (EUT) contends that when people are faced with uncertain or risky outcomes, they make a decision by estimating the expected utility (and not the expected value) of each probable outcome. Daniel Bernoulli initiated the EUT in 1738, when he solved the famous St Petersburg paradox. The paradox portrays a situation where people are asked to state the amount they are willing to pay for a fair coin toss game. At each toss, they are paid twice the amount they were paid at the previous toss every time heads appears; but if tails appears in a given stage, they are not entitled to any gain in that stage. The toss is assumed to be repeated infinitely. Although the expected value of the gain in such a game is infinite and, therefore, people should be willing to pay any price to participate, it is observed that it is not the case, hence the paradox. Bernoulli advocates that people do not actually assess the outcome of the game in terms of expected value, but in terms of the expected satisfaction they would derive from winning each additional toss. In other words, they make the decision to pay or not to pay based on their expected utility. (Bernoulli, 1738; translated from Latin to English by Dr. Louise Sommer, 1954).

As mentioned earlier, capital market theory assumes that investors are risk averse and their decisions are guided by the goal to maximise their expected utility. Behavioural finance, on the contrary, argues that this not always the case. The most famous case against EUT is the prospect theory.

2.8.1 Prospect Theory

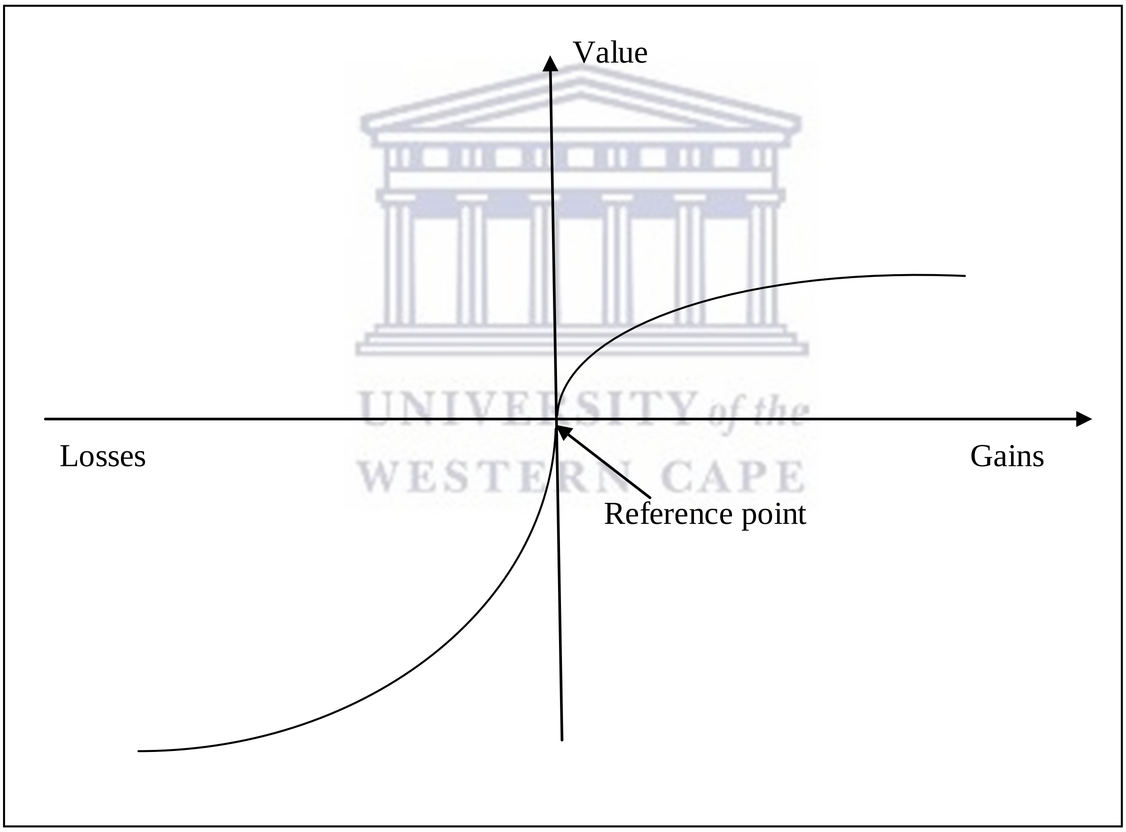
Kahneman and Tversky (1979) formulate the prospect theory as an alternative theory to EUT. While EUT asserts that decision-making is based on the expected utility of the final outcome, prospect theory advocates that decision-making is based on an estimation of the potential value of gain and losses, instead of the final outcome. Since people value gains and losses differently and underweight probable outcomes compared to outcomes deemed certain, this results in risk avoiding decisions when gains are known with certainty and in risk loving decisions when losses are known with certainty (certainty effect).

Kahneman and Tversky (1979) illustrate the certainty effect using several examples, two of which are presented below. 95 respondents are faced with two problems. Problem 1 involves an alternative choice between a gain of 4,000 with a probability of 0.8, and a gain of 3,000 with a probability of 1. Meanwhile, Problem 2 involves an alternative choice between a loss of 4,000 with a probability of 0.8, and a loss of 3,000 with a probability of 1. For Problem 1, 80% of the respondents choose the sure 3,000 gain over the 4,000 gain with 0.8 probability, although the latter has a higher expected value. Conversely, for Problem 2, 92% of the respondents select the 4,000 loss with 80% chance over the sure loss of 3,000. In other words, people shy away from risk when they expect a sure gain, but are willing to take risk to avoid a sure loss. The authors conclude that people are risk averse when faced with choices that involve gains and risk seeking when they have to choose between options that involve losses.

Kahneman and Tversky (1979) rely on the results of the above experiments to propose a graphical representation of the changes in the potential value assigned to gains and losses by people, called the value function, depicted in Figure 2.4 below. The reference point, found at the intersection of the gains/losses axis and the value axis, is the initial wealth (utility) position of the decision maker prior to taking their decision. The function exhibits a concave shape for gains, showing that people are risk averse when it comes to choices involving gains. Conversely, the function is convex for losses, meaning that people are risk seeking when outcomes involve losses. Interestingly, the value function is flatter in the area of gains than in the area of losses. This means that the satisfaction derived from gaining is lower than the dissatisfaction experienced from losing an equivalent amount of wealth. This behaviour towards losses and gains is referred to as loss aversion.

Kahneman and Tversky (1979) contend that the prospect theory comprises two distinct phases with respect to the decision-making process, namely editing, which is the first stage, and evaluation, which is the second one. Editing deals with examining the prospects at hand in order to simplify them and ease the evaluation stage. Meanwhile, evaluation involves selecting the prospect that exhibits the highest value. The editing phase encompasses several operations, including coding, combination, segregation, cancellation, simplification, and dominance detection.

Figure 2.4: The Value Function



Source: adapted from Kahneman and Tversky (1979)

Coding is the operation used by people to define outcomes in a gains/losses scale. What is viewed as gains or losses depends on the present wealth position of the decision-maker, which is their reference point. Then, gains correspond to amounts received while losses refer to amounts paid. Combination occurs when people blend probabilities of choices that present similar outcomes, in order to simplify the evaluation process. Meanwhile, segregation comes into play when it is possible for the decision-maker to identify a risk-free element (lowest gain or loss that is to be received or paid with certainty) and a risky element (extra gain or loss that might be received or paid) in the choice at hand and to split the two. Besides, cancellation is usually implemented when the decision-maker is faced with choices that all contain a common prospect. In this case, the common prospect is cancelled such that the focus is placed on the distinguishing prospects. People operate simplification when they round up or down probabilities associated with outcomes, or the outcome itself. Prospects which are deemed to yield the lowest value are considered dominated, and are disregarded by the decision-maker. In the evaluation phase, the decision-maker works out the value of each option, using the potential outcomes and their assigned probabilities. Next, they select the option that carries the highest value (Kahneman and Tversky, 1979).

The editing and evaluation stages of the decision-making process discussed above show that people do not usually based their decisions solely on facts, but also on their perceptions, judgments, experiences, and emotions, towards the situation faced. As a result, the decision they make and their subsequent behaviour are tainted with cognitive biases.

2.8.2 Behavioural Biases

The competitive and fast-paced nature of financial markets exposes investors to lots of information and complex situations they have to analyse, and make decisions as fast as possible. To achieve this, investors usually simplify these complex situations by focusing on peculiar aspects and disregarding the others. These mental shortcuts they use are known as heuristics. Most of the time, this approach to decision-making works well; however, it often results in systematic errors, termed cognitive biases. Tversky and Kahneman (1974) identify three heuristics used by people to estimate probabilities and values, and which lead to several cognitive biases: representativeness, availability, and anchoring and adjustment.

Representativeness heuristics is observed in instances where people make decisions based on the similarity of the current situation or event with a previous one, regardless of the probability of occurrence or the size of the sample the current event falls into. For example, an individual would be categorised as a lawyer based on the extent to which their description is similar to that, or is representative, of a typical lawyer. People are subject to availability heuristics when they estimate the likelihood of the occurrence of an event based on how easy they can remember similar events, regardless of how infrequent the event actually happens. Investors using availability heuristics tend to make decisions following the information or events they can easily remember, instead of analysing all the information relevant to the situation or problem faced. Anchoring is a situation in which an answer is guessed by making estimates from an available number, which has either been proposed initially or which stems from an incomplete calculation. As the original number (the anchor) is set, estimates are made around it to guess a plausible final answer by either upward or downward adjustments. However, the anchor usually influences and biases the estimate of the final answer, as differing initial points lead to differing final answers (Tversky and Kahneman, 1974).

Some of the most prominent cognitive biases which stem from the above heuristics and which investors are subject to are discussed below.

Overconfidence, which refers to people's tendency to overrate their skills in terms of forecasting and decision-making, is a common bias among investors. Similarly, when investors overestimate the likelihood of occurrence of an event, they are subject to overconfidence. Gervais and Odean (2001) find that overconfidence builds up from investors' prior successes. As investors experience success in their trades, they become more confident, and end up overestimating their investment skills and their forecast accuracy. Overconfidence can lead to flawed decision-making and, consequently, to poor investment performance.

Herd behaviour is observed when investors make decisions based on a collective trend on the market, irrespective of the path their rational judgment dictates them to follow. In other words, the investors follow the crowd. Herd behaviour is emotion-driven and, therefore, not rational. Stock market bubbles and crashes originate from herd behaviour (Lux, 1995).

Regret aversion is a decision behaviour adopted when people do not want to deal with negative emotions in case a decision they made results in an unsatisfactory outcome. Larrick and Boles (1995) argue that because investors do not want to feel regret of a poor investment move they made, or they do not want to report a loss, they tend to hold on to underperforming stocks. Moreover, investors are more inclined to hold stocks of well-established companies rather than those of less well-known companies as they perceive that they will feel less regret if the price of the former goes down subsequently.

Framing is a phenomenon whereby people react differently towards a situation, in function of the way in which the situation is portrayed (framed). Tversky and Kahneman (1981) find that people's decisions change depending on whether a problem is laid out in terms of potential gains or in terms of potential losses (money issues or human lives). More specifically, people are more cautious in decision-making when presented with a problem from a potential gains perspective. However, they are more reckless when the same situation is framed in terms of potential losses.

The heuristics and biases presented above influence investors' decision-making process and lead them to exhibit irrational behaviour, which usually translates on financial markets in the form of overreaction and underreaction.

2.8.3 Overreaction Hypothesis

The overreaction hypothesis posits that investors tend to exhibit extreme reactions to new and unexpected information arriving on the stock market, resulting in erratic variations in stock prices and subsequent corrections. According to DeBondt and Thaler (1985), overreaction occurs because investors focus more on recent information in making their investment decisions, while giving less relevance to earlier fundamental data.

DeBondt and Thaler (1985) test the overreaction hypothesis on the U.S. stock market in a study carried out on the New York Stock Exchange (NYSE) and covering the period from January 1926 to December 1982. Winner portfolios refer to portfolio comprised of stocks that have earned the highest cumulative excess returns over the past 36 months, while loser portfolios refer to portfolios made up of stocks with the lowest cumulative excess returns over the past 36 months. The study reveals that over the examination period, losers yield cumulative excess returns of 19.6% on average, 36 months post-formation, while winners underperform the market by 5% on average, resulting in an average cumulative abnormal return (ACAR) of 24.6%. In their follow-up study, DeBondt and Thaler (1987) confirm the reversal behaviour of winners and losers in the U.S. over the period 1926 – 1982. More importantly, they find that the magnitude of the reversal effect is so large that it cannot be fully explained by risk changes as defined by the CAPM. Instead, the effect aligns with the overreaction explanation.

Lakonishok, Shleifer, and Vishny (1994) and Dreman and Lufkin (2000) argue that investor overreaction drives the value premium on stock markets, thereby affirming that the value anomaly results from irrational behaviour. Studies such as Spyrou, Kassimatis, and Galariotis (2007) in the UK, Wu (2011) in China, and Hsieh and Hodnett (2011) in South Africa, provide evidence of investor overreaction on capital markets.

2.8.4 Underreaction Hypothesis

The underreaction hypothesis contends that investors' reactions to new and unexpected information or events are slow and, sometimes, inefficient to bring prices back to equilibrium. Investor underreaction has been uncovered mainly through event studies. A study by Bernard and Thomas (1990) on stock price reaction to earnings announcements reveals that adjustments in stock prices following earnings announcement in a given quarter do not reflect potential changes in subsequent quarterly earnings. Rather, investors tend to rely on prior year quarterly earnings levels to predict earnings levels for a corresponding quarter in the current year. As a result, they fail to adjust their forecasts immediately after earnings announcements. In other words, they underreact to new information. In the same vein, Abarbanell and Bernard (1992) show that analysts slowly react to earnings announcements. When positive earnings are released, they are likely to expect the positive trend to continue and, therefore, keep their earnings forecasts too high over the next three quarters subsequent to the announcement. Similarly, if negative earnings are released, analysts tend to keep their forecasts for the forthcoming quarters too low.

Michaely, Thaler, and Womack (1995) investigate the impact of dividends announcements on stock prices and find that stock prices slowly adjust to announcement of dividends. Ikenberry, Lakonishok, and Vermaelen (1995) show that the market underreacts to stock buyback announcements, and portfolios of stocks subject to the repurchase yield outperform the market four years after the announcement. In a more recent note, Frazzini (2006) finds that the tendency of investors to sell a stock too soon following good news or to hold on to it for too long following bad news (disposition effect) results in a situation where prices adjust too slowly to the arrival of new information. Besides, Fabozzi, Fung, Lam, and Wong (2013) argue that erratic fluctuations in stock prices may lead to underreaction as the market processes the unexpected and extreme movements at a slow pace. Lastly, Li (2018) shows that since investors face attention issues, their inattention may drive underreaction of prices to new information. However, the author points out that the underreaction tends to be weaker when investors consider the information to be relevant enough to devote most of their attention to it.

In conclusion, because investors are mainly driven by emotions, they do not always behave rationally. They are subject to cognitive biases which make them react either too fast or too slow to new and unexpected information coming to their attention. As a result, stock prices deviate from their equilibrium, hence market anomalies. In other words, anomalies are not driven by risk, but originate from stock mispricing.

2.9 Conclusion

The above discussion has presented the foundations of both traditional finance and behavioural finance, which underlie today's investment theories and practices. Traditional finance portrays investors as rational beings who are risk averse and whose ultimate objective is to maximise their utility. They seek the highest returns for a given level of risk, or a given level of returns for the lowest level of risk, and are willing to bear more risk only if they are rewarded with higher returns. Indeed, movements in stock prices are unpredictable and prices quickly adjust to the infusion of new and unexpected information in the market, in such a way that investors are not able to consistently yield above-average returns. The only way to do so is to accept more risk. The concepts of investor rationality and market efficiency have provided a conducive platform for the development of asset pricing models designed to estimate and explain returns on assets in the market. These include the CAPM and subsequent multifactor models that have attempted to remedy its weaknesses, such as the APT, the Fama-French three-factor model, and the Carhart four-factor model.

Indeed, empirical studies have uncovered patterns in average stock returns that the CAPM does not account for, later known as market anomalies, with the most notable ones being size, value, and momentum anomalies. The rationale behind these anomalies has been subject to debates. While proponents of market efficiency propose risk-based arguments whereby investors' willingness to bear higher risk calls for a risk premium, behaviourists propose behaviour-based arguments, citing cognitive biases as well as over- and underreaction of investors as the main causes of stock mispricing.

CHAPTER 3 – REVIEW OF PRIOR LITERATURE

3.1 Introduction

The Capital Asset Pricing Model (CAPM) of Sharpe (1964), Lintner (1965), and Mossin (1966) predicts a positive linear correlation between a stock's exposure to systematic risk and its returns. However, soon after the CAPM was developed, researchers observed patterns in stocks returns not captured by CAPM's beta. These unexplained patterns were then termed anomalies. Three major anomalies have been given particular attention over the years and studied extensively, namely size, value, and momentum anomalies.

The size effect refers to the observation that companies with small market capitalisation (small caps) tend to earn higher risk-adjusted returns than companies with large market capitalisation (large caps) on average in the stock market. The value effect designates the phenomenon whereby companies with high fundamental-to-price ratios (called value stocks) generally outperform their low fundamental-to-price ratios counterparts (called growth stocks). Lastly, the momentum effect is all about the tendency of companies which have performed well in the past (past winners) to keep performing well in future while those which have experienced poor results in the past (past losers) continue to perform poorly in future.

These anomalies have been empirically tested over the years from different perspectives. One of the strongest motivations of these empirical tests was to determine whether these anomalies exist on capital markets out of the period of study when they were first identified, and whether they persist over the years. Another perspective of study was to design asset pricing models which could describe the patterns induced by these anomalies in the cross-section of stock returns. This led to the design of the well known three-factor model of Fama and French (1993) and to the four-factor model of Carhart (1997). Lastly, studies researched the cause of such anomalies, with two prominent views being risk and mispricing.

This chapter discusses the evidence pertaining to size, value, and momentum anomalies on international and South African markets, along with major style-based multifactor models which have been devised to capture their effects in average stock returns. The chapter then reviews the literature related to the cyclical behaviour of these anomalies, before concluding with the main empirical evidence on their possible explanation.

3.2 Evidence of Size, Value, and Momentum on Capital Markets

A significant amount of research has been carried out to test the existence of size, value, and momentum anomalies on capital markets, both internationally and in South Africa. While a significant body of literature provides evidence of the presence and pervasiveness of these anomalies on capital markets, a few studies contend that they are non-existent or have disappeared over time.

3.2.1 International Evidence

Decades of studies have investigated the presence of market anomalies on international capital markets, starting with the size effect which was first documented on the U.S. stock market by Banz (1981).

3.2.1.1 Size Effect

Banz (1981) carries out a study covering the period 1926 – 1975 in which he analyses the return behaviour of common stocks traded on the New York Stock Exchange (NYSE), in relation to their market value (market capitalisation). For the purpose of the study, he constructs arbitrage portfolios by longing small caps (bottom market cap quintile) and shorting large caps (top market cap quintile). The study reveals that such portfolios outperform the market by 19.8% annually on average (t-stat = 2.99) on a risk-adjusted basis, over the examination period. Interestingly, the author raises the question of whether small caps outperforming large caps is due to size itself or to size-correlated unknown factors. Nevertheless, Banz attributes the size effect to flaws in the CAPM, and does not view it as a sign of market inefficiency.

The existence of the size effect on the U.S. stock market is confirmed by Reinganum, in a study from 1963 to 1977 Indeed, Reinganum (1981) finds a statistically significant size premium of approximately 19% per annum on average over the examination period. In addition, he aligns with Banz (1981) with regard to the cause of the longevity of the effect. Other studies such as Brown, Kleidon, and Marsh (1983), Fama and French (1992, 1993), and Hou and van Dijk (2018), support the presence of the size effect in the U.S. However, Brown et al. (1983) uncover instability in the size effect over the period 1967 – 1979 and suggest that the magnitude of the effect might be time-sensitive.

Evidence of the size effect is equally uncovered outside the U.S. stock market. A study by Annaert, Crombez, Spinel, and Van Holle (2002) on common stocks from 15 European markets over the period from 1973 to 2000 reveals that the outperformance of small caps towards large caps averages roughly 19% annually during the examination period. This performance is quite similar to the ones documented in the U.S. Rouwenhorst (1999) conducts a study on factors that influence stock returns on 20 emerging markets over the period 1975 – 1997 and reports a strong average monthly size premium of about 0.7%.

Despite the compelling evidence of the existence of the size effect, some studies have uncovered evidence against the latter. Fraser (1995) analyses stock returns on the London Stock Exchange during the period 1970 – 1991 and finds that small caps do not consistently outperform the market subsequent to 1989. He therefore concludes that the size effect has vanished after 1989. Horowitz, Loughran, and Savin (2000a) find that the return differential between large caps and small caps traded on the U.S. stock market becomes statistically insignificant when microcaps are excluded from the sample over the period 1963 – 1981. In a follow-up study, they show that the relation between size and realised returns is inconsistent during the period 1980 – 1996 in the U.S. (Horowitz, Loughran, and Savin, 2000b). They conclude that the size effect is dead after the 1980s. A similar conclusion is reached by Schwert (2003) in the U.S., in a study covering the period 1982 - 2002.

However, van Dijk (2011) reviews the body of literature on the size effect and concludes that it is premature to declare its demise. Indeed, evidence of the size effect is provided by recent studies such as Schmidt, von Arx, Schrimpf, Wagner, and Ziegler (2017), and Asness, Frazzini, Israel, Moskowitz, and Pedersen (2018), among others. More specifically, Schmidt et al. (2017) find a significant decile-based and quintile-based size premium in the U.S. market and several European markets in a study spanning the period 1986 – 2012 and covering 23 countries. In the same vein, Asness et al. (2018) document a strong and stable size premium over the period 1926 – 2012 (for US data) and 1983 – 2012 (for the other 23 developed markets) in all 24 international markets under investigation.

3.2.1.2 Value Effect

The value anomaly has been extensively investigated on international markets. In the U.S., Basu (1977) documents the value effect by analysing the average returns on stocks and their price-earnings (P/E) ratios, in a study covering the period 1956 – 1971. The study reveals that the bottom P/E quintile portfolio yields an average annual return of 16.3% while its top P/E quintile counterpart exhibits an average annual return of only 9.3% over the study period. The study by Basu (1983) provides further evidence of the value anomaly in the U.S. as he finds that top 20% earnings yield (E/P) portfolios generate a monthly risk-adjusted return of 1.38% while their bottom 20% counterparts yield a mere 0.72% monthly return, on average, over the study period 1963 – 1979. These findings lead the author to question the validity of the CAPM, as he contends that the value premium observed stems from a misspecification of the asset pricing model.

Fama and French (1992) further document the value effect in the U.S., using the book-to-market (B/M) ratio as proxy. In a study spanning the period 1962 – 1989, the authors find that the average monthly return differential between the portfolio of value stocks (top B/M decile) and the portfolio of growth stocks (bottom B/M decile) stands at roughly 1.53%. Lakonishok, Shleifer, and Vishny (1994) equally establish the existence of the value effect in the U.S. market, as they uncover a significant value premium over the period 1963 – 1990.

Fama and French (1998) uncover the value premium on international markets in a study encompassing 13 markets around the world, over the period from 1975 to 1995. The markets under investigation include the U.S. and 12 countries located in Europe, Australia, and the Far East (EAFE). Using B/M equity sorts, growth stocks (bottom B/M tercile) are found to be outperformed by value stocks (top B/M tercile) both in and outside the U.S. The return differential between global value and growth stock portfolios stand at 7.68% per annum on average (statistically significant at 1% level). Sorts on earnings yield, dividend yield, and cash-flow-to-price equally provide similar results. Moreover, the value effect is also found to be prevalent and pervasive on emerging markets (Japan, Hong Kong, and Singapore). These findings, along with the results uncovered by Davis, Fama, and French (2000), reveal that the value effect is neither sample- nor period-specific. Rouwenhorst (1999) corroborates the findings by Fama and French (1998). Indeed, he finds that a global value-minus-growth portfolio yields an excess return of 9% per annum on average (significant at 1% level) on emerging markets, which is close to the return of 7.68% documented by Fama and French (1998) on developed markets.

More recent findings equally align with the above evidence of the value effect on international capital markets, including Annaert et al. (2002), Chan and Lakonishok (2004), Fama and French (2012), Asness, Moskowitz, and Pedersen (2013), and Desban and Jajir (2016).

However, as with the size effect, some studies disagree with the pervasiveness of the value effect on international markets. Schwert (2003) reports that over the period 1994 – 2002, value portfolios underperform the market in the U.S. He argues that the value effect tends to have vanished, or at least diminished in the 1990s. He suggests as probable cause of this disappearance (or attenuation) the increased activity of arbitrageurs trying to profit from these anomalies and, consequently, leading the market to be more efficient. Chordia, Subrahmanyam, and Tong (2014) uncover evidence supporting Schwert's (2003) conclusion.

More specifically, Chordia et al. (2014) investigate the effects of inflated trading volumes and rise in trading activity (arbitrage) on the persistence of selected anomalies (including the value anomaly, proxied by B/M) on the U.S. market over the period 1976 – 2011. Using ordinary least squares (OLS) regressions, they find that a strategy long on value stocks (top B/M decile) and short on growth stocks (bottom decile B/M) yields an extremely significant monthly return close to unity throughout the study period. However, when they control for liquidity and arbitrage trading, they notice that the value premium shrinks by half through the examination period, but is still statistically significant, probably due to limits to arbitrage trading.

However, Auer and Rotman (2018) challenge the conclusions put forth by Chordia et al. (2014). In a study spanning the period from 1990 to 2017 and covering 21 capital markets (including the U.S.), they analyse the relationship between stock trade volume and returns on arbitrage portfolios based on size, value, momentum, and beta. Using quantile regressions coupled with a Markov regime-switching model, they find no consistent negative correlation between liquidity and returns on an arbitrage value portfolio and conclude that arbitrage trading is not likely to explain movements in the value premium.

Cotter and McGeever (2018) document a decline in the value premium in the UK over the period 1990 – 2013. The average monthly return of the B/M hedge portfolio falls from a strong 1.18% for the sub-period 1990 – 2001 to a weak 0.49% for the sub-period 2002 – 2013. The authors attribute this disappearance phenomenon to the improvements in the efficiency of financial markets over time, therefore aligning with Schwert (2003).

3.2.1.3 Momentum Effect

The momentum effect was first documented in the U.S. by Jegadeesh and Titman (1993). Using data for the period 1965 – 1989, they find that a momentum investment strategy that consists of longing prior 3- to 12-month past winners while shorting 3- to 12-month past losers yields a monthly risk-adjusted return ranging between 1.31% and 1.49%. These results are confirmed in their 2001 study with a longer study period (1965 – 1998), in which the momentum strategy implemented earns approximately 1.4% per month on average throughout the period (Jegadeesh and Titman, 2001).

Recent evidence of the existence and pervasiveness of the momentum effect on U.S. capital markets is provided by Fama and French (2012), Novy-Marx (2012), Asness et al. (2013), and Zaremba (2018), among others. However, Novy-Marx (2012) contends that the momentum effect is primarily rooted in stock medium-term past performance and not recent past performance. He shows that momentum strategies built on intermediate past performance (12 to 7 months prior returns) outperform strategies based on recent past performance (6 to 2 months prior returns). Besides, the aforementioned recent studies equally investigate momentum outside the U.S., as discussed below.

Evidence of the momentum effect is equally documented on European and emerging markets. Rouwenhorst (1998) finds that winners outperform losers on 12 European stock markets by roughly 1% per month on average, over the period 1980 – 1985, which is similar to findings by Jegadeesh and Titman in the U.S. (1993, 2001). Using an international dataset comprised of 23 countries grouped under four headings (North America, Europe, Asia-Pacific, and Japan), Fama and French (2012) discover strong monthly returns from a momentum strategy long on past winners and short on past losers, which average 0.92% in Europe over the period from 1989 to 2011. These monthly returns are close in magnitude to the ones uncovered by Rouwenhorst (1998) and, therefore, support the claim that there is a momentum effect on European markets. Asness et al. (2013) and Zaremba (2018) equally report strong momentum effect in Europe.

Rouwenhorst (1999) reports the momentum effect on 20 emerging markets for the period 1982 - 1997, though it is weaker than on developed markets. The lower return is attributed to the lower number of stocks included in winner and loser portfolios. Cakici, Fabozzi, and Tan (2013) document a significant momentum premium in Asia and Latin America, while Zaremba (2018) reveals a strong momentum effect on major African and Asian markets.

However, recent research argues that the momentum effect is disappearing. Hwang and Rubesam (2008) examine the persistence of momentum premium on U.S. stock markets in a study spanning the period 1927 – 2006. The study reveals that momentum returns have not been consistent over the examination period. More specifically, the premium has been positive and significant from 1940 to 1965 and from 1975 to 1999. However, it has slowly weakened from a significant average of 1.13% per month in the late 1990s to an insignificant average of 0.87% per month in mid 2000s. The authors challenge the conclusions by Jegadeesh and Titman (2001), arguing that though the momentum effect was present in the 1990s, it has been fading away since then. They attribute the disappearance of the anomaly to the increase in hedge funds and arbitrage trading after 1990.

Bhattacharya, Kumar, and Sonaer (2012) follow up on the study by Hwang and Rubesam (2008) and break down their study period (1965 – 2010) into three sub-periods, matching the examination period by Jegadeesh and Titman (1993) (1965 – 1989), Jegadeesh and Titman (2001) (1990 – 1998), and a more recent sub-period 1999 – 2010. Their findings show that momentum returns are significant in the first sub-period, less significant in the second one, but diminish to insignificant proportions in the last one. Their results, thus, concur with Hwang and Rubesam (2008). They cite improved market efficiency as the main reason for the disappearance of the effect in the U.S. Chordia et al. (2014) equally document a diminishing momentum effect in the U.S., while Cotter and McGeever (2018) get to a similar conclusion in the UK.

The above literature reveals that size, value, and momentum effects have been present on international markets since they were first identified. However, the magnitude of the style premiums has varied over time.

3.2.2 South African Evidence

The existence of size, value, and momentum anomalies has also been investigated and documented on the Johannesburg Stock Exchange (JSE), though the South African literature is less impressive.

With regard to the size effect, van Rensburg (2001) analyses the pattern embedded in stock returns on industrial companies on the JSE, over the period from 1983 to 1999, in order to uncover the style factors that describe those returns. Using a list of 23 candidates grouped into value, future earnings and growth, and irrationality, the study implements a portfolio-based approach and identifies 11 style-based effects which explain the expected returns on industrial shares on the JSE, over the study period. The effects which stand out of the crowd include size, value, and momentum. Small caps (bottom market cap terciles) outperform large caps (top market cap terciles) by approximately 1.1% per month, both on an unadjusted and a risk-adjusted basis, at a 1% statistical significance. In a follow-up study, van Rensburg and Robertson (2003a) analyse style effects on stock returns on the JSE, between 1990 and 2000. The study makes use of 24 candidates and implements a characteristic-based approach. Findings confirm the existence of the size effect left unexplained by the CAPM. Van Rensburg and Robertson (2003b) investigate the relation between the size and value effects and beta on the JSE. Using quintile breakpoints, they find that small firms earn on average higher returns than large firms over the study period, but exhibit lower risk. They equally report that size and value effects are independent to each other.

Basiewicz and Auret (2009) research evidence of size and value effects on the JSE over the period 1992 – 2005 while controlling for liquidity and trading costs. Univariate and multivariate tests uncover a strong size premium, which is consistent with findings by van Rensburg (2001) and van Rensburg and Robertson (2003a, 2003b). Subsequent studies such as Strugnell, Gilbert, and Kruger (2011), Hoffman (2012), Hodnett, Hsieh, and van Rensburg (2012), Hammar (2014), and Hsieh (2015) reveal the existence of the size effect on the JSE. However, Strugnell et al. (2011) highlight that the size effect might be fading away on the JSE, but the results are not conclusive. Meanwhile, Hammar (2014) notes that the size effect was not present in all of the years of his examination period.

Recent evidence against the persistence of the size effect on the JSE is provided by Auret and Cline (2011). Indeed, the study investigates whether the size, value, and January anomalies exist on the JSE, through the period 1988 - 2006. Findings show that the size premium is statistically insignificant over the study period. The authors suggest that this contradictory result may stem from different study periods and datasets, given that the study focuses not only on industrial shares as earlier studies, but on the JSE ALSI stocks as a whole. Muller and Ward (2013) contend that there is no size effect on the South African market, except for micro caps, which represent only 1% of the market value of the JSE. Similarly, Page, Britten, and Auret (2016) find no significant size premium on the JSE, concluding that the effect has largely diminished over time. Page and Auret (2018) adjust size portfolios for liquidity and transaction costs and find that small caps underperform large caps, unlike Basiewicz and Auret (2009) who instead find that the size effect persists after controlling for liquidity and trading costs.

The value effect has equally drawn considerable attention on the South African market over the years, as authors investigate its pervasiveness and the more suitable fundamental-to-price ratio that should be used as proxy for the anomaly. Fraser and Page (2000) examine the ability of value and momentum strategies to predict returns on industrial stocks on the JSE, during the period 1973 – 1997. Using dividend-to-price ratio (D/P) and book-to-market ratio (B/M) as proxies for the value effect and quintile breakpoints, they find that the return differential between value and growth portfolios is statistically significant and averages roughly 0.6% per month, for both D/P and B/M portfolios, over the examination period. Notwithstanding, returns on B/M portfolios are stronger than those on D/P portfolios. Lastly, value and momentum effects operate independently to each other on the JSE.

Van Rensburg (2001) also documents a strong value premium on the JSE. Indeed, he reveals that a long-short value-growth strategy yields a strong monthly return of 1.41% and 1.21% when portfolios are sorted on earnings-to-price ratio (E/P) and D/P respectively. In other words, E/P returns are stronger than D/P returns and, therefore, E/P should be used as proxy for the value effect on the JSE. Van Rensburg and Robertson (2003a) confirm this conclusion as they report that price-earnings ratio (P/E) subsumes D/P and cash-flow-to-price (C/P) on the JSE. In the same year, they document the independence of size and value anomalies on the South African stock market (van Rensburg and Robertson, 2003b).

However, van Rensburg and Robertson (2003a) do not investigate the suitability of B/M as proxy for the value effect. Thus, building on this research gap, coupled with Fama and French's (1992) conclusion that B/M is a better proxy than E/P, Auret and Sinclaire (2006) analyse the explanatory power of the two aforementioned value proxies on the JSE, in a study spanning from 1990 to 2000. They find that when B/M is included in the size-P/E model of van Rensburg and Robertson (2003a), the P/E-portfolio returns become insignificant. They conclude that B/M better captures the value effect in the cross-section of stock returns on the JSE. Their results therefore concur with Fama and French's (1992) findings in the U.S., but contradict van Rensburg and Robertson's (2003a) conclusions in South Africa.

Auret and Sinclaire's (2006) conclusions are supported by Basiewicz and Auret (2009). Indeed, the latter compare the value premium of arbitrage portfolios long on value stocks and short on growth stocks, formed on E/P, C/P, and B/M. They discover that the B/M strategies generate the largest premiums while E/P strategies yield the smallest ones. However, the magnitude of the value premiums is lower than in previous studies, and the authors attribute this phenomenon to adjustments made for trading costs and liquidity in their study. Strugnell et al. (2011), Hoffman (2012), Muller and Ward (2013), Page at al. (2016), and Page and Auret (2018), among others, report a consistent and significant value premium on the JSE.

Contrary to the above studies which document a persistent and significant value effect in South Africa, Auret and Cline (2011) find that the value premium, proxied by B/M, is not statistically significant on the JSE. Hammar (2014) and Hsieh (2015) equally report mixed results. More specifically, Hammar (2014) asserts that over the period 1999 – 2012 and using quartile breakpoints, value portfolios outperform growth portfolios when portfolios are sorted on P/E and price-to-cash-flow ratio (P/CF), whereas growth stocks outperform value stocks when portfolios are constructed on price-to-book ratio (P/B) and dividend yield (D/Y). However, the author does not attempt to provide an explanation for this mixed result, arguing that the purpose of the study is to find evidence of value (and size) effect on the JSE.

Hsieh (2015) echoes the above findings by Hammar (2014) as he reveals that value portfolios sorted on E/P and sales-to-price ratio (S/P) perform better than their growth counterparts. Conversely, growth portfolios sorted on book-to-price (B/P) yield higher risk-adjusted returns than their value counterparts. The study covers the period 2004 – 2013 and uses tercile breakpoints. More importantly, Hsieh (2015) notices that both value and growth effects are statistically insignificant or significant at 10% level; in short, they are weak over the study period, thereby concurring with Auret and Cline (2011). The author points to differences in methodology (use of tercile breakpoints) and examination period (including the 2008 financial crisis) as possible reasons for his contrasting results.

Most studies on market anomalies in the South African context have reported a significant momentum premium. According to Fraser and Page (2000), the return differential in average performance between 12-month prior winners and 12-month prior losers stands at 0.76% per month, one month after portfolio formation throughout the study period. The performance is significant at 1% level. Findings by van Rensburg (2001) accord with the above results. As a matter of fact, he reports a consistent and significant average momentum premium of 1.52% and 1.07% for portfolios formed based on 12-month prior returns on the JSE, depending on whether the stocks were ranked based on positive past prices only or using the whole stock sample respectively. Van Rensburg (2001) equally documents a momentum premium for six-month and three-month prior return portfolios, but they are not as strong as the premium from 12-month past return portfolios.

Hoffman (2012) carries out a study designed to identify selected stock market anomalies on the JSE. The study covers the period from 1985 to 2010, and the anomalies under review include size, value, momentum, profitability, asset growth, net share issues, accruals, and momentum. The study provides evidence of the momentum effect on the JSE. Indeed, Hoffman finds that future stock returns are positively correlated to prior 12 months stock returns, in such a way that a momentum strategy would yield a monthly return in the range of 1.4% to 2.5%. The positive relationship is strong in all size groups, except for micro caps, and is observable even after controlling for the size and the value effects. The study argues that the negative correlation between future stock returns and momentum in micro caps may mean that the latter is more prone to mean reversion than stocks in other size groups. Hodnett et al. (2012) align with previous South African studies as they find a significant momentum premium for portfolios based on past 12-month returns. Prior 12-1-, 24-, and 6- portfolios equally exhibit a momentum premium on the JSE.

Muller and Ward (2013) carry out a study similar to Hoffman's (2012) on the JSE in which they analyse the effect of approximately 10 style variables on average stock returns, among which the momentum effect, over the period from 1985 to 2011. They find that a prior 12-month momentum portfolio with a holding period of 3 months consistently outperforms the market index by approximately 10% on average over the examination period, while the annual average return on winners-minus-losers portfolios stands at 18.6%. Further studies such as Page et al. (2016) and Page and Auret (2017, 2018) reveal a significant and consistent momentum premium on the JSE.

Surprisingly, van Rensburg and Robertson (2003a) disagree with Fraser and Page (2000) and van Rensburg (2001) as they affirm that their study does not uncover any significant momentum effect on the JSE. According to them, the discrepancy may result from the fact that they use all JSE shares as sample instead of industrial stocks only. However, this reason may not hold, given that subsequent studies (for example, Hoffman, 2012; Muller and Ward, 2013) use a broader sample than industrial stocks; yet, they uncover a significant momentum effect on the JSE. The argument put forth by Page, Britten, and Auret (2013) to explain their mixed results seems more convincing. Indeed, they find that over the period from 1995 to 2010, momentum profits have decreased by about 1% towards the second half of the study period, and attribute this shrink to the 2008 financial crisis.

The above discussion reveals that overall, South African evidence concurs with international evidence with respect to the presence and consistency of size, value, and momentum anomalies on stock markets. Although a few studies conclude otherwise, the impressive literature that documents the pervasiveness of these anomalies in financial markets shows that they deserve more attention, especially since they reflect patterns in stock returns not explained by the well-known CAPM. To this effect, several style-based multifactor asset pricing models have been devised over the last 30 years to capture the premiums embedded in stock returns and induced by the aforementioned anomalies.

3.3 Size, Value, Momentum and Style-Based Asset Pricing Models

Style-based multifactor asset pricing models augment the original Capital Asset Pricing Model (CAPM) with risk factors, the purpose of which is to account for style risk premiums left unexplained by the market risk factor of the CAPM. The multifactor models which have witnessed particular focus in the financial literature over the years include the Fama-French (1993) three-factor model, Carhart (1997) four-factor model, and more recently, the Fama-French (2015) five-factor model.

3.3.1 Fama-French (1993) Three-Factor Model

Following the evidence by Fama and French (1992) that the CAPM is not able to capture the size effect and the value effect reflected in stock returns on the U.S. stock market, Fama and French (1993) augment the CAPM with a size and a value risk factors designed to explain the patterns associated with these anomalies and observed in average stock returns. In order to construct the two factors for their study spanning the period 1963 - 1991, they rank their U.S. stock sample according to market capitalisation and break down the sample into 2 groups, termed small (S) and big (B). Similarly, they rank their sample according to stocks' book-to-market equity (BE/ME) and break the sample into 3 groups, known as low (L), medium (M), and high (H) BE/ME. This procedure results in six value-weighted portfolios as size and BE/ME groups intersect (S/L, S/M, S/H, B/L, B/M, and B/H). The size risk factor (SMB) is calculated as the difference between the average of returns on the small-cap portfolios and the returns on the big-cap portfolios. Meanwhile, the value risk factor (HML) is computed as the difference between the average of the returns on the high BE/ME portfolios and the returns on the low BE/ME portfolios. In other words, the size effect is proxied by an arbitrage portfolio long on the small-cap portfolio and short on the big-cap portfolio, while the value effect is proxied by an arbitrage portfolio long on the high BE/ME portfolio and short on the low

BE/ME portfolio; hence the risk-based explanation of size and value effects propounded by the authors.

Fama and French (1993) show that their three-factor model exhibits a stronger explanatory power than the CAPM in the U.S., as the two additional factors explain much of the movements in stock returns missed by the CAPM. The authors confirm these results three years later still on the U.S. market; however, the three-factor model fails to explain the short-term momentum effect (Fama and French, 1996). Arshanapalli, Coggins and Douglas (1998) test the Fama-French three-factor model over 18 capital markets covering North America, Europe, and Asia, over the period from 1975 to 1995. Consistent with Fama and French (1993, 1996), they report that the three-factor model captures most of the fluctuations in average stock returns observed in the U.S. They document a similar result in European and Asian markets.

International studies carried out by Griffin (2002), Moerman (2005), and Fama and French (2012), among others, document the suitability of Fama-French three-factor model in explaining stock returns in the U.S., European, and emerging markets. However, they contend that country-specific risk factors provide a better description of stock returns than global risk factors. Further studies such as Bahtnagar and Ramlogan (2012) and Choi (2017) support the superior explanatory power of Fama-French three-factor model over CAPM in the U.S. and in the UK respectively.

Despite the convincing evidence provided above with respect to the ability of Fama-French three-factor model to better explain patterns in stock returns on international markets, few studies conclude otherwise. Halliwell, Heaney, and Sawicki (1999) test the explanatory power of the Fama-French three-factor model on the Australian stock market, using data covering the period 1981 - 1991. The study reveals a weak explanatory power of the model in Australia, contrasting with subsequent findings as discussed above. Equally, Nwani (2015) uncovers an insignificant size effect in the UK and concludes that firm size may not be a reliable factor in describing the cross-section of stock returns on the London Stock Exchange.

With regard to the South African stock market, Basiewicz and Auret (2010) test the Fama-French three-factor model on the JSE, over the study period 1992 – 2005. They find that the model explains the variations in stock returns significantly and is, therefore, a suitable asset pricing model. Moreover, the study shows that the three-factor model does a better job in estimating average returns than the CAPM. The ability of the Fama-French three-factor model to capture variations in average stock returns on the JSE is supported by other studies such as Sacco (2014), Mahlophe (2015), and Tony-Okeke (2015). Sehgal, Subramaniam, and Deisting (2014) find supporting evidence that the CAPM performs poorly in explaining average returns in South Africa, while the three-factor model of Fama and French exhibits a better explanatory power. However, they report that the latter does not capture stock return patterns related to the momentum effect, which concurs with the findings by Fama and French (1996) in the U.S.

Despite the fact that the above studies have provided evidence of the suitability of the Fama-French three-factor model to explain average returns on the JSE, few studies disagree with those findings. Boamah (2015) investigates the performance of the Fama-French three-factor model (and the Carhart four-factor model) on the South African market, over the period 1996 – 2012. The study reveals that the three-factor model does not fully explain the returns related to size and value (proxied by B/M ratio). Boamah concludes that the three-factor model is not suitable in explaining stock returns on the JSE and, therefore, should be used with caution. He further states that the disagreement between his findings and those of Basiewicz and Auret (2010) may result from the longer examination period of his study, or from the use of better tests. A study by Karp and van Vuuren (2017) supports the non-suitability of Fama-French three-factor model to describe stock average returns on the South African stock market. The reasons put forth to explain the poor performance of the models include liquidity issues, inadequate market proxies, volatility, and unpriced risk factors.

3.3.2 Carhart (1997) Four-Factor Model

Motivated by the short-term momentum effect of Jegadeesh and Titman (1993) and the earlier evidence of the inability of the three-factor model of Fama and French to capture the momentum premium (see Fama and French, 1996), Carhart (1997) builds a style factor designed to capture momentum profits in the cross-section of stock returns in the U.S. He adds the factor to the Fama-French three-factor model to form a four-factor model.

Carhart (1997) examines the performance of U.S. mutual funds over the period 1962 – 1993 in order to determine whether such performance results from superior stock selection or from common factors present in the returns on stocks as well as differences in trading costs and expenses incurred by mutual funds. In order to build the momentum factor, he ranks the sample of funds according to their past 12-month returns and breaks down the ranked sample into three groups. The factor is then constructed as the difference between the average returns of the top prior 12-month return terciles (known as winner portfolio) and the average returns of the bottom prior 12-month return terciles (known as loser portfolio).

The study reveals that over the examination period, longing prior year top 10% mutual funds while shorting prior year bottom 10% mutual funds generates an annual return of 8%, of which 4.6% is explained by the momentum effect and captured by the associated factor. In other words, the added momentum factor improves the explanatory of the three-factor model. Carhart concludes that the persistence of mutual fund performance is driven by common factors embedded in stock returns coupled with differences in trading costs and expenses of mutual funds. However, he does not conclude on the risk interpretation of his newly devised style factor.

Subsequent to Carhart's (1997) study, Bello (2008) compares the explanatory power of the CAPM, Fama-French three-factor model, and Carhart four-factor model in predicting the returns of U.S. active equity mutual funds, over the period 1986 – 2006. Consistent with Fama and French (1993) and Carhart (1997), findings show that the three-factor model better describes returns on mutual funds than the CAPM, while the four-factor model is a better predictor of returns than the three-factor model. Fama and French (2012) support these findings in the international setting, as they report that a global version of Carhart four-factor model performs better than their three-factor model in explaining stock returns (except for Japan), though they equally claim that the former still misses significant patterns in stock returns.

Kassimatis (2008) finds that the Carhart four-factor model exhibits a much stronger explanatory power than the CAPM in Australia when risk premiums are considered static. However, when the latter are allowed to vary with time, the four-factor model loses its power. Chen and Fang (2009) argue that the four-factor model performs poorly in Asian markets - corroborating Fama and French (2012) in Japan – whereas Czapkiewicz and Wojtowicz (2014) contend that the four-factor model is a better predictor of stock returns than the three-factor model on the Polish stock market.

Despite the limited South African literature on the ability of the Carhart four-factor model to capture style-based effects in stock returns on the JSE, most of the research carried out corroborates the international evidence. Sacco (2014) investigates the accuracy of CAPM, Fama-French three-factor model, and Carhart four-factor model in determining the cost of equity on the JSE for the period 2002 – 2012. The study reveals that the four-factor model outperforms the other two models in terms of explanatory power and its performance reflects the most the performance of the ideal asset pricing model. Mahlophe (2015) tests the suitability of the Fama-French three-factor model and Carhart four-factor model in capturing market anomalies in the various sectors of the JSE over the period 2002 – 2014. She finds that the four-factor model explains variations in stock returns very well in four sectors out of the six under investigation. Moreover, the four-factor model exhibits a stronger explanatory power than the three-factor model. Further studies, including Tony-okeke (2015) and Small and Hsieh (2017), among others, equally conclude that the Carhart four-factor model does a good job in describing stock returns on the JSE. However, Boamah (2015) finds that the Carhart four-factor model performs poorly in explaining stock returns in South Africa.

3.3.3 Fama-French (2015) Five-Factor Model

Fama and French (2006, 2008) find that the stock return patterns related to profitability and investment are not fully captured by their three-factor model. These findings, coupled with the growing literature on the significant relationship between profitability, investment, and average returns, motivate Fama and French to suggest a five-factor model of asset pricing. This model augments the three-factor model with two additional factors designed to explain the profitability and investment effects (Fama and French, 2015). Results show that the five-factor model exhibits a superior explanatory power on the U.S. stock market, as compared to the three-factor model (Fama and French, 2015). However, the model fails the GRS test (Gibbons, Ross, and Shanken, 1989), suggesting that it sill misses some patterns embedded in stock returns. Fama and French (2016) investigate whether their five-factor model explains selected anomalies not initially targeted by their three-factor model, including momentum. However, the model fails to capture the latter.

Subsequent studies outside the U.S. to test the improved ability of the five-factor model to explain average returns provide mixed results. For example, Cakici (2015) reveals that the five-factor model provides significant improvement over the three-factor model in North America (U.S. and Canada) and Europe, but not in Japan and Asia Pacific. The positive results on European markets is supported by studies including, among others, Chiah, Chai, Zhong, and Li (2016) and Huynh (2018) in Australia, Fama and French (2017) in developed European markets, Zaremba and Czapkiewicz (2017) and Foye (2018) in European emerging markets, and Foye (2018) in Latin America.

With respect to Asian markets, further studies equally document the failure of the five-factor model to significantly improve over the three-factor model in describing stock returns. Indeed, Jiao and Lilti (2017) find on the Chinese stock market that the model does not do a better job than the three-factor model in explaining stock returns. Fama and French (2017) and Kubota and Takehara (2018) report an indistinguishable amelioration by the five-factor model over the three-factor model in Japan, while Foye (2018) uncovers similar results in Asian markets as a whole. Finally, Fama and French (2017) contend that their five-factor model performs poorly in Asia Pacific, aligning with Cakici (2015), but disagreeing with Chiah et al. (2016) and Huynh (2018) with respect to Australian markets. Fama and French (2017) argue that this failure on Asia Pacific markets may result from poor integration of asset pricing in the region.

Besides, Fama and French (2015) show that the value risk factor loses its power in the five-factor model, though they argue that the redundancy might be specific to the sample used in the study. In this regard, Chiah et al. (2016) find that the value risk factor is not redundant on the Australian stock market, while Jiao and Lilti (2017) reach a similar conclusion in China.

Tests of the recent Fama and French (2015) five-factor model on the JSE are limited. Mahlophe (2015) investigates the performance of the five-factor model on the JSE and finds that it exhibits a stronger explanatory power than the Fama-French three-factor model. Furthermore, the study reveals that the value risk factor tends to be redundant when the profitability and investment factors are added to the three-factor model. These results align with the findings by Fama and French (2015) on the U.S. stock market. Charteris, Rwishema, and Chidede (2018) report lower pricing errors when the five-factor model is implemented on the JSE, though they claim that the errors are still significant, thereby echoing Fama and French (2015) in the U.S.

In summary, most of the asset pricing literature reveals that the three-factor model of Fama and French (1993) significantly improves the description of stock returns as compared to the CAPM, by capturing the patterns related to size and value anomalies. The results are consistent in both international and South African studies, even though some studies report contrasting results. Moreover, the literature documents the ability of the Carhart (1997) four-factor model to explain the momentum effect and, consequently, to be a superior model to the Fama-French three-factor model, while the recent Fama-French (2015) five-factor model improves the explanatory power of the three-factor model. However, tests of the five-factor model outside the U.S. in terms of explanatory power provide mixed results, and further tests might be necessary to come to a definite conclusion.

3.4 Cyclicality of Size, Value, and Momentum Effects

The earlier discussion on the existence and persistence of size, value, and momentum effects on stock markets revealed that the presence of the anomalies has been stronger over certain periods than others, suggesting that the style spreads associated to these effects might be time-varying, or cyclical. Thus, a significant number of studies has analysed the behaviour of size, value, and momentum effects over different economic and market conditions in the U.S. and beyond.

Krueger and Johnson (1991) examine the sensitivity of the size (and value, proxied by P/E) anomaly to U.S. market conditions over the period 1975 – 1984. They find that the size effect is stronger during bull and expansionary periods than during bear and recessionary periods, even after controlling for market risk. Consequently, small cap portfolios outperform large cap portfolios during bulls and expansions, but underperform the latter during bears and contractions. Thus, the size premium varies with business conditions and, therefore, investors should be aware of the prevailing business conditions before adopting an investment style.

Bhardwaj and Brooks (1993) echo the findings by Krueger and Johnson (1991) with respect to the cyclicality of the size effect. More specifically, they investigate the magnitude of the size premium over the various phases of the economic cycle, in a study encompassing U.S. stocks and covering the period 1926 - 1988. They report that small caps outperform large caps during bull periods, but underperform them during bear periods. Besides, small caps exhibit higher total risk than large caps, which may indicate that the excess returns generated by small caps over large caps is a compensation for higher risk embedded in small stocks. More recent studies equally document the sensitivity of the size effect to economic conditions in the U.S. They include, among others, Perez-Quiros and Timmermann (2000), Kim and Burnie (2001), Lucas, van Dijk, and Kloek (2002), Switzer (2010), Scheurle and Spremann (2010), and Switzer and Pickard (2016).

Outside the U.S., Liew and Vassalou (2000) reveal that the size premium and future economic growth are positively correlated on developed markets (U.S., Canadian, Australian, and European markets). Rutledge, Zhang, and Karim (2007) find that small stocks perform better than large stocks during bull markets, but worse during bear markets, on the Chinese stock market, aligning with U.S. evidence. Switzer (2010) and Switzer and Pickard (2016) report similar results in Canada, while Sarwar, Mateus, and Todorovic's (2017) findings in the UK support the time-varying size premium story in the U.S.

Turning to the cyclicality of the value effect, Krueger and Johnson (1991) show that in the U.S., value portfolios (low P/E portfolios) yield higher excess returns than growth portfolios (high P/E portfolios) in bear and recessionary periods. The authors argue that this phenomenon may signify that growth companies struggle to maintain their growth rate in earnings above that of the market in bad times. As with the size effect, they conclude that the value premium is sensitive to business conditions prevailing at a given point in time.

Xing and Zhang (2005) investigate the cyclicality of economic fundamentals with regard to value and growth manufacturing companies on U.S. markets, over the period 1963 – 2002. The fundamentals under consideration include dividend growth, earnings growth, sales growth, profitability, investment growth, and investment rate. The study reveals that overall, value stocks (top B/M quintiles) fundamentals experience a stronger decline than those of growth stocks (bottom B/M quintiles) during recession periods. In other words, the value premium is larger in poor economic states, which is consistent with results reported by Krueger and Johnson (1991).

Kwag and Lee (2006) also document a cyclical effect in the value premium as they find that the value-growth spread is higher during recessionary periods in the U.S. These results are confirmed by Athanassakos (2009) who reports that over the period 1985 – 2005, value stocks outperform growth stocks in both economic expansions and recessions; however, the value premium is larger in recession periods and bear markets. Scheurle and Spremann (2010), and Gulen, Xing, and Zhang (2011), among others, confirm the cyclical behaviour of the value effect on U.S. stock markets.

Liew and Vassalou (2000), in their study covering the U.S., Canada, Japan, Australia, and 6 European markets over the period 1978 – 1996, discover that the value premium varies with the economic cycle. However, the premium is pro-cyclical on U.S. and European markets, while it is counter-cyclical in Australia, Canada, and Japan. These results are inconsistent with U.S.-based studies which report a counter-cyclical relationship between the value premium and business conditions. Athanassakos (2009) documents a stronger value premium in poor economic conditions in Canada, supporting Liew and Vassalou's (2000) findings, while Bayramov (2013) reports that the value premium is higher in economic expansions than in economic recessions in Europe, thereby aligning with Liew and Vassalou (2000).

With respect to tests on the sensitivity of the momentum premium to business conditions, Chordia and Shivakumar (2002) examine momentum profits on the U.S. stock market in relation to phases of the economic cycle, over the period 1926 - 1994. They note that on average, momentum strategies earn profits during economic expansions and suffer losses during recessions. Cooper, Gutierrez, and Hameed (2004) investigate the relationship between market states and the magnitude of momentum profits in the U.S. over the period 1929 – 1995. They find that momentum profits are economically large and statistically significant subsequent to up markets (periods of favourable market returns) whereas they are small (or negative) and insignificant following down market states (periods of unfavourable market returns). In a follow-up study, Asem and Tian (2010) assert that movements in momentum premium are related to market conditions. However, they only partially concur with Cooper et al. (2004), since they demonstrate that momentum profits emerge when the market state remains unchanged, whether up or down, and not only following up market states. They attribute this phenomenon to investor overconfidence that builds up when the market persists in the same direction. Findings by Kim, Roh, Min, and Byun (2014), and Daniel and Moskowitz (2016), among others, support the pro-cyclical behaviour of the momentum premium in the U.S. However, studies such as Liew and Vassalou (2000), and Scheurle and Spremann (2010), claim to find no support in favour of the cyclicality of the momentum effect in the U.S.

Liew and Vassalou (2000) equally argue that the return differential between momentum returns in favourable and unfavourable market conditions is weak and statistically insignificant on European markets, hereby concluding that there is no evidence of cyclical behaviour with respect to the momentum effect. These results contrast with the majority of U.S. evidence, but is supported in the UK by Sarwar et al. (2017), who reveal that momentum profits during expansionary and recessionary periods are not significantly different.

Moving to South Africa, the literature pertaining to the cyclicality of size, value, and momentum premiums is limited. Graham and Uliana (2001) investigate the existence of the value effect on the JSE for the period running from 1987 to 1996, using the price-to-book ratio (P/B) as proxy. The results show that value portfolios (bottom 50% P/B stocks) underperform their growth counterparts (top 50% P/B stocks) in the first half of the examination period and outperform them in the second half. According to the authors, this cyclical performance of value stocks might result from events that occurred in the 1990s and reshaped the political and economic environments of the country.

Hodnett (2014) examines the pattern of the value premium on the JSE in order to determine whether it exhibits a cyclical behaviour. The study spans over the period 1997 – 2013 and use as benchmarks E/P, B/P, and S/P. Findings reveal that the median ratio for portfolios formed on S/P experience the highest volatility over the examination period, suggesting that the value premium measured based on S/P ratios is more likely to vary following fluctuations in business conditions on the JSE. In a follow-up study, Hsieh (2015) finds that value stocks yield higher returns than growth stocks during bull periods, but experience greater losses than the latter during bear periods. This finding contradicts the bulk of U.S. evidence whereby value stocks outperform growth stocks during bear periods. Barnard and Bunting (2015) study the behaviour of the size and value effects on the JSE over the period 2006 – 2012 and report that during the 2008 market downturn, the size effect vanishes (large caps outperform small caps) while value stocks outperform growth stocks. These findings are consistent with international evidence. However, they do not investigate the cyclicality of momentum premium, claiming that the anomaly mostly reflects a liquidity effect.

Conclusively, the international evidence suggests that size, value, and momentum anomalies are cyclical in nature. While the size and momentum effects are more prominent during bull and expansionary periods, the value effect is stronger during bear and recessionary periods. In the South African context, the distinction is less clear-cut since the available studies provide mixed results. This leaves room for further studies on the cyclical behaviour of these anomalies on the JSE. Notwithstanding, the rationale behind the cyclicality (and the overall existence) of these anomalies remains a debated topic in the asset pricing literature, with the two major propositions being a risk-based explanation and a behaviour-based explanation.

3.5 Size, Value, and Momentum Premiums: Risk or Mispricing?

Studies on the explanation of size, value, and momentum premiums have been conducted mainly on international markets, more specifically in the U.S. On the one hand, proponents of market efficiency argue that style premiums are compensation for risk not captured by CAPM's beta. On the other hand, proponents of behavioural finance contend that style premiums reflect security mispricing.

3.5.1 Style Premiums as Compensation for Risk

In a U.S. study covering the period 1956 – 1985, Chan and Chen (1991) investigate the reasons behind the asymmetries in risk and returns between small stocks and large stocks. They demonstrate that small stocks are companies that have performed poorly lately, experiencing weak operational efficiency and high financial leverage. As a result, investors perceive them to be riskier than large companies and would venture in such distressed companies only if they were compensated with a premium for bearing higher risk. Fama and French (1992, 1993, 1995, and 1996) equally argue that the size effect is linked to economic fundamentals. More specifically, it is linked to profitability, as small stocks exhibit lower profits than large caps. However, Fama and French (1993, 1995) caution that the size effect was mostly caused by the recession in the early 1980s, which translated into a prolonged period of low profits for small caps. Liew and Vassalou (2000) document a positive correlation between the size premium and future economic growth on developed markets and conclude that their results support a risk-based rationale for the size premium.

According to Amihud (2002), small caps are riskier than large caps because they are less liquid. His U.S. study spanning the period 1963 – 1997 reveals that as small caps exhibit low liquidity and higher trading costs, investors demand higher returns to purchase portfolios of small stocks. Thus, the size premium compensate (partially) for the liquidity risk embedded in small caps. Studies such as Pastor and Stambaugh (2003), and Acharya and Pedersen (2005), among others, equally cite liquidity risk as the reason behind the size premium. Meanwhile, Perez-Quiros and Timmermann (2000), Hwang, Min, McDonald, Kim, and Kim (2010), and Sarwar et al. (2017) attribute the size premium to credit risk attached to small stocks.

The risk-based view of the value effect is propounded by Fama and French (1992, 1993) who show that the value risk factor (along with the size risk factor) proxies for common macroeconomic risk factors reflected in average stock returns on U.S. stock markets. Fama and French (1993, 1995, and 1996) argue that value stocks (high B/M stocks) are distressed firms which experience low profits in a consistent manner. In other words, they carry a higher fundamental risk than growth stocks (low B/M stocks) and, as a result, command higher expected returns on the part of investors. Liew and Vassalou (2000) adopt a risk-based explanation for the value effect since they establish that the value premium is positively correlated to economic growth in North America and Europe, hence reflecting some macroeconomic risks.

Building on Fama and French (1995), Zhang (2005) investigates the source of the value premium and posits that the premium arises because of higher operating risk experienced by value stocks, especially in poor economic states. Indeed, the author shows that companies are generally faced with higher costs when they have to scale down their investment in operating fixed assets than when they have to expand it (cost reversibility). Given that value firms sit with more fixed assets which become unproductive during recession periods, they want to scale down their long-term investment more than growth companies in such periods. However, cost reversibility limits their scaling down capacity, thereby increasing their operating risk as compared to growth firms. The increase in operating risk causes a rise in value companies' discount rate in economic downturns, lowering further their earnings prospects. These two phenomena render value stocks fundamentally riskier than growth stocks, hence the value premium.

Peltomäki and Äijö (2015) analyse the exposure of value and momentum anomalies to volatility risk in the U.S. over the period 1990 – 2013, and find that the value premium increases when volatility risk is high (recession periods) and decreases when volatility risk is low (expansion periods). They conclude that the value premium is primarily driven by volatility risk and is, therefore, a compensation for exposure to the latter. This result is confirmed on the French market by Arisoy (2010). Several other studies have demonstrated that the value premium is risk-driven, such as Vassalou and Xing (2004), Xing and Zhang (2005), Kapadia (2011), Chui, Titman, Wei, and Xie (2012), and Cakici and Tan (2014).

Turning to the momentum anomaly, Conrad and Kaul (1998) provide a hint for the risk-based rationale, in their study on the U.S. market covering the period from 1926 to 1989. They investigate the profitability and source of profits of about 120 investment strategies, and find that a major determinant of momentum profits is the dispersion in average returns of individual stocks included in the portfolios involved in the momentum strategies considered. This suggests that the momentum premium is driven by stocks' total risk and is, thus, a compensation for bearing this risk. Chordia and Shivakumar (2002) contend that the momentum premium results from macroeconomic risks. Indeed, they note that momentum profits vanish when macroeconomic variables (yield on Treasury bills, default spread, term spread, and dividend yield) are controlled for in stock returns.

More recently, Avramov, Chordia, Jostova, and Philipov (2013) investigate the relationship between financial distress and the profitability of momentum strategies (among others) in the

U.S. over the period 1985 – 2008 and discover that momentum profits are generated by shorting stocks experiencing high credit risk and whose credit conditions are worsening. Indeed, these profits disappear when those companies are excluded from the study sample. The authors conclude that momentum premium compensates for credit risk. Peltomäki and Äijö (2015), and Daniel and Moskowitz (2016) suggest that momentum profits could be compensation for volatility risk. However, Daniel and Moskowitz (2016) claim that a behavioural approach could also fit the explanation for the premium. Ruenzi and Weigert (2018) report that momentum returns are driven by the crash risk inherent to momentum portfolios, hence providing a risk-based explanation for the momentum premium.

3.5.2 Style Premiums as Manifestation of Mispricing

The behavioural explanation of anomalies has mostly been directed towards value and momentum effects, leaving similar interpretations for the size anomaly quite unexplored (van Dijk, 2011). Notwithstanding, Daniel and Titman (1997), in their study on the U.S. market covering the period 1973 - 1993, discover that after controlling for firm size, factor loadings on Fama and French's (1993) size-mimicking portfolio fail to explain returns. The authors, therefore, suggest that the size effect is driven by the charasteristics of the firm and not by risk factors, hereby giving credit to the mispricing explanation of the size effect.

Hou and Moskowitz (2005) suggest investors' underreaction as plausible behavioural rationale for the size effect. Analysing the impact of market frictions on stock returns in the U.S. over the period 1963 – 2001, they report that the delay experienced by stock prices to adjustments to new information and caused by investors' underreaction results in a premium, which partly explains the size effect. Indeed, given that small stocks are not followed as closely as large stocks on the market, their prices tend to reflect new information more slowly than large stocks, hence driving the size premium. Following Chan and Chen (1991), van Dijk (2011) suggests that the size effect might result from investors overreacting to past poor performance of small caps by extrapolating the poor performance too far in future. Thus, when the overreaction is corrected, the size premium emerges. However, he is not aware of any study of this kind. Hur, Pettengill, and Singh (2014) advocate that since distress risk does not explain the size effect, either idiosyncratic risk or behavioural factors should be the driver(s) of the size premium.

With respect to the irrational view for the value effect, Lakonishok, Shleifer, and Vishny (1994) argue that investors' irrational behaviour drives the value premium. More specifically, using book-to-market decile portfolios, they examine the performance of value and growth strategies on the U.S. stock market over the period 1963 – 1990, and report that value strategies earn 10% to 11% higher average annual returns than growth strategies over the study period. They claim that the value – growth spread is so large that it cannot be justified solely by fundamental risk, considering that performance measures controlling for risk fail to fully explain the differential. According to the authors, investors tend to over-extrapolate past good performance of growth stocks and past poor performance of value stocks, leading to an excessive purchase of growth stocks and sell-off of value stocks. This overreaction drives down the price of value stocks while pushing up that of growth stocks. Eventually, when the market becomes aware of the mispricing, reversal occurs, resulting in the value premium. Similar studies, such as Haugen (1995) and MacKinlay (1995), support the view that the value premium is extremely large for a risk-based explanation.

Daniel and Titman (1997) equally investigate the value premium from a risk / non-risk based perspective and find that the expected return on a stock tends to be more determined by its book-to-market characteristics than by the risk inherent to the stock. They report that the HML factor loading of Fama and French (1993) fails to explain the stock return when the firm's book-to-market characteristic is controlled for. Daniel, Titman and Wei (2001) report similar findings on the Japanese stock market while van Rensburg and Robertson (2004) equally conclude that a characteristic-based approach tends to better explain the value effect than a risk-based approach on the JSE.

Findings by Daniel, Hirshleifer, and Subrahmanyam (2001) concur with Lakonishok et al.'s (1994) view of the value premium. Indeed, the authors find that the value premium is the result of a joint risk and mispricing effect, since the market risk factor (CAPM's beta) and a mispricing factor jointly describe stock returns accurately. They further argue that the mispricing is caused by investors' overconfidence about their information processing and investing skills, leading to overreaction and subsequent correction of stock prices.

More recently, Fong (2012) demonstrates that the value premium is not related to macroeconomic risk and, therefore, cannot be explained from a risk-based perspective. This finding contradicts most of the results supporting the risk-based view (for example, Fama and French, 1992, 1993, 1995). Hwang and Rubesam (2013) echo the findings by Lakonishok et al. (1994) as they report that the value premium originates from the price reversal following investors' overreaction to new information. Meanwhile, Chen and Shin (2016) show that the value premium is largely determined by investor sentiment; but they acknowledge that part of the premium can equally be explained by fundamental risk, hence aligning with Lakonishok et al. (1994) and Daniel et al. (2001).

Considering the behavioural view of the momentum anomaly, Chan, Jegadeesh, and Lakonishok (1996) investigate whether the profitability of momentum strategies results from investors' underreaction to unexpected information regarding earnings. The study, which covers U.S. data and spans the period 1977 – 1993, reveals that performance of winner and loser stocks persists for at least six months following the release of earnings news, whether good or bad, before any adjustments take place. More interesting, past winners which have performed poorly lately keep outperforming the market for at least one year following bad earnings news. The authors argue that this phenomenon challenges the risk-based rationale and attribute it to the slow reaction of the market to act on new and unanticipated information coming in. Results by Chan et al. (1996) are supported by Daniel, Hirshleifer, and Subrahmanyam (1998) and Barberis, Shleifer, and Vishny (1998), who show that the momentum premium is driven by investors' underreaction to newly available information on the market.

Studies by Griffin, Ji, and Martin (2003) on international markets (Americas, Europe, Asia, and Africa), Cooper et al. (2004), and Asem and Tian (2010) on U.S. markets, report that macroeconomic risk variables are unable to capture momentum profits, thereby contrasting with findings by Chordia and Shivakumar (2002) in the U.S. Therefore, they refute a risk-based rationale for the momentum premium to the benefit of a mispricing explanation. Daniel and Moskowitz (2016) assert that momentum premiums generated from strategies profiting from momentum crashes cannot be fully explained by volatility risk or crash risk and should, consequently, be partly driven by behavioural phenomena such as investors' fear of losses in turbulent times. McLean and Pontiff (2016) analyse over 90 variables (including size, value and momentum) across approximately 80 academic papers, which have been shown to be reliable predictors of stock average returns. Using a strategy long on top quintiles and short on bottom quintiles on each variable under investigation, the study reveals that on average, the returns dissipate by 26% on long-short out-of-sample portfolios and by approximately 32% subsequent to the publication of the study, suggesting that the returns generated by the portfolios built on those predictors are more likely driven by data mining and mispricing.

In a nutshell, the debate surrounding the rationale behind size, value, and momentum anomalies with the inherent premiums is ongoing. Advocates of market efficiency assert that the style premiums are rewards for higher risk whereas proponents of behavioural theories claim that the premiums are driven by security mispricing. As the issue remains unsolved, a further study pertaining to the rationale of size, value, and momentum premiums could shed light on the topic in the South African context.

3.6 Conclusion

Extensive research has been carried out on financial markets with regard to size, value, and momentum effects. Studies conducted on international markets and in South Africa have documented for the most part the existence and persistence of these anomalies. A peculiar issue pertaining to the value effect has been to identify the best measure of the latter on the JSE. Studies by Auret and Sinclaire (2006) and Basiewicz and Auret (2009) have shown that the book-to-market ratio (B/M) is the best proxy for the value effect on the JSE, subsuming the explanatory power of the other measures, and particularly the price-earnings ratio (P/E) advocated by van Rensburg (2001) as the best measure for value.

The inability of the CAPM to explain the size, value, and momentum effects (hence called anomalies) has prompted researchers to design multifactor models which would capture these effects in the cross-section of stock returns, with the most prominent ones being the Fama-French (1993) three-factor model, Carhart (1997) four-factor model, and Fama-French (2015) five-factor model. The models have been found to perform well both internationally and on the JSE in describing stock returns, although some evidence has suggested the contrary.

Contradictory evidence with respect to the presence of size, value, and momentum effects on capital markets have led researchers to question whether they might possibly be time-varying. Research about the cyclical nature of these effects has shown that in general, size and momentum effects are pro-cyclical whereas the value effect is counter-cyclical.

A major outstanding issue in the anomaly literature remains the underlying reasons for their existence. The risk-based view argues that the anomalies reflect reward for higher risk borne by investors. For example, they are shown to be associated with macroeconomic risks, liquidity risk, credit risk, and volatility risk, among others. However, the irrational view affirms that the anomalies primarily reflect security mispricing induced by investors' under- and overreaction on financial markets. Nevertheless, the latter view does not refute the possibility that the anomalies can be partly explained by risk.

CHAPTER 4 – DATA AND METHODOLOGY

4.1 Introduction

The review of the underpinning theories of asset pricing and market anomalies, coupled with the discussion related to the empirical evidence pertaining to size, value, and momentum anomalies, has uncovered a couple of issues. Research on the existence of the aforementioned anomalies on the Johannesburg Stock Exchange (JSE), as well as the ability of multifactor asset pricing models to explain them is relatively limited as compared to international studies and, more importantly, has generated more divergent results. Furthermore, the cyclical behaviour of size, value, and momentum effects, which has been established by empirical studies on international markets, has been granted little attention on the JSE. Lastly, the rationale behind the style effects, whether they are driven by risk or, rather, reflect security mispricing, tends to be overlooked in the South African literature on market anomalies.

In this regard, this study, as outlined in chapter 1, purports to investigate the presence of size, value, and momentum effects on the JSE, establish the suitability of multifactor asset pricing models to capture the variations in stock returns induced by those anomalies, assess the cyclicality of style-based effects on the South African market, and examine their rationale from a risk-based perspective in the context of the JSE.

This chapter aims at describing the data used and outlining the methodology implemented to achieve the objectives of the study. More specifically, the chapter opens with a detailed explanation of the choice of the examination period and of the research sample. The chapter then proceeds with the methodology adopted to construct portfolios and devise the asset pricing models designed to test the existence, cyclicality, and risk-driven nature of size, value, and momentum effects, as well as the ability of style-based asset pricing models to explain the latter. The chapter closes with a review of the biases the study is subject to and steps undertaken to reduce their effect on the results of the study.

4.2 Data

This section discusses the reasons that motivated the choice of the examination period, and outlines the specifics of the research sample.

4.2.1 Study Period

The study spans the period from 1 January 2002 to 31 December 2018 (204 months). The choice of the study period is relevant from many perspectives. The beginning of the examination period coincides with the aftermath of the restructuring of the Johannesburg Stock Exchange (JSE) that occurred during the late 1990s and early 2000s, and which aimed at rendering the exchange more competitive and more efficient. Indeed, according to Mkhize and Msweli-Mbanga (2006), in a view to aligning with global standards, the JSE and the London Stock Exchange (LSE) entered an agreement in 2001 which resulted in the creation of the Securities Exchange Trading System, abbreviated as SETS, in May 2002. The new trading system, housed in London, replaced the Johannesburg Equities Trading, also known as JET, which has been in use since its introduction in 1996. Thanks to SETS, market participants were able to execute and report trade orders faster as the system was able to handle large volumes of transactions and executions were automatic. More important, information pertaining to transactions in the system was transmitted instantly and more accurately, thereby improving the efficiency of the JSE. The improvements brought by SETS attracted more investors into the JSE, and this in turn led to the enhancement of the liquidity of the exchange, as a result of the mitigation of the thin trading issue.

Furthermore, the JSE restructuring enabled the creation of the FTSE/JSE All-Share Index (ALSI) in June 2002. The ALSI includes the top JSE-listed companies in terms of market capitalisation, and represents 99% of the JSE main board (FTSE Russell Factsheet, 2018). This point is particularly relevant as the index is considered to be representative of the JSE and has therefore been used in most South African studies as the market proxy (see for example Strugnell, Gilbert and Kruger, 2011; and Hsieh, 2015). The present study equally adopts the ALSI as the market proxy.

Finally, the examination period is comprehensive as it covers the various phases of the South African business cycle as identified by the South African Reserve Bank (SARB). Venter (2005) provides details of the criteria considered in the determination of the South African business cycle turning points, by building on earlier works by Burns and Mitchell (1946) and

Moore (1980). More specifically, Burns and Mitchell (1946) define business cycles as movements observed in a country's macroeconomic activities, starting with expansions happening simultaneously in several economic sectors, and continuing with recessions and then recoveries which announce the next cycle. The authors further assert that a business cycle lasts anything between from more than 1 year to 10 or 12 years and cannot be segmented into shorter periods with similar magnitudes. The major implication of the above definition is that the identification of reference turning points in the business cycle should account for 3 main criteria including the duration, the amplitude, and the scope of the trend.

For example, Moore (1980) claims that a trend should be considered as an expansion or a contraction if it is observed for 6 months at least. Besides, economic trends should be considered as recessions or expansions if they witness a decrease or an increase in all major activities in the economy. Moreover, given that cycles cannot be segmented into shorter periods, a fall in the level of activity that occurs during an upward phase should qualify as a downward phase if its duration is the same as the shortest historically recorded downward phase. Finally, as trends in business cycles involve the whole economy, it is not possible to determine turning points through the analysis of only one economic variable like the gross domestic product (GDP).

As an illustration of how the aforementioned criteria play out in the determination of the phases of the business cycle, Venter (2005) shows that the falls in the aggregate level of economic activities that were observed in 2001 and at the end of 2002 in the South African economy were never recognised as downward phases because the trends failed to meet the scope and amplitude criteria.

According to Venter (2005), the South African Reserve Bank (SARB) determines the turning points in the business cycle using a combination of major macroeconomic variables as well as significant events affecting the economy. The major variables involved in the determination of turning points include the leading, coincident, and lagging business cycle indicators, coupled with the current diffusion index and the historical diffusion index, when the aforementioned composite indicators reveal a high probability of the existence of a turning point. The turning points break down the business cycle into an upward phase and a downward phase. The upward phase refers to a period in which several business activities experience a growth rate higher than the long-term trend in economic growth. Conversely, the downward phase designates a period in which several business activities experience a slowdown or a growth rate lower than the long-term trend in economic growth. In its September 2018 quarterly bulletin, the SARB identified two business cycles between 1999 and 2018. Therefore, with respect to the examination period of this study, the following phases have been specified: two upward phases (January 2002 – November 2007, and September 2009 – November 2013) and two downward phases (December 2007 – August 2009, and December 2013 - December 2018).

Actually, the study period covers the booming period experienced by the South African economy in the early 2000s until late 2007 when the U.S. real estate bubble burst, plunging the financial sector and then the global economy into an unprecedented crisis in 2008. The South African economy rebounded in late 2009 thanks to the revival of the commodity sector (Kantor, 2018). However, the South African economic trend reversed again in late 2013 and has since been pacing downward due, among other things, to political uncertainty which has eroded investor confidence. The economy entered a recessionary period in the third quarter of 2018 before re-emerging in the fourth quarter of the year, but at a lower growth rate than expected (Stats SA, 2018). In conclusion, the examination period is long enough to observe significant variations (if any) in style effects under investigation, namely size, value, and momentum.

It is worth mentioning that a few researchers criticise the SARB's approach to the identification of the turning points because of the institution's delay in making the indicators available to the public. More specifically, Boshoff and Binge (2017) claim that the SARB may take up to 2 months to publish its leading indicator after the month of reference, and up to 24 months to establish the business cycle turning points after the events that triggered the turn occurred. Thus, they contend that the analysis of the business cycle as conducted by the SARB is unlikely to be useful in terms of forecasting and decision-making. However, the focus of this study is to establish the cyclicality of the style effects on the JSE; thus, the argument of whether the approach used is suitable for business forecasting is not addressed here.

4.2.2 Research Sample

The research sample is comprised of common stocks of companies included in the FTSE/JSE All-Share Index (ALSI). The ALSI index, which is made up of 164 companies as at 31 December 2018, represents about 99% of the market value of all of the securities quoted on the JSE main board (FTSE Russell Factsheet, 2018). Thus, the constituents of the ALSI provide an accurate picture of the South African stock market. The research sample accounts for ALSI constituents throughout the examination period. In this regard, suspended or delisted stocks in the sample over the study period are included and followed up until the delisting or suspension date, after which they are excluded from the sample. This procedure frees the sample from survivorship bias. However, some stocks are excluded from the sample for the following reasons:

- Missing accounting data (46)
- Less than 24-month accounting data (04), which is required for the calculation of the investment factor in the Fama-French five-factor model
- Negative book value (01), excluded following the methodology by Fama and French (1993).

It should be noted that the above data adjustments have equally been used in prior South African studies (see for instance Basiewicz and Auret, 2010). Consequently, adopting a similar methodology provides comparative grounds for the findings from this study and those from previous ones.

The data adjustments lead to the exclusion of 51 companies from the sample, leaving a final sample of 208 companies, which represents 42432 (208x17x12) observations considered for the study.

The list of ALSI constituents is obtained from the JSE, while their monthly closing prices, market capitalisation, and dividend yield are obtained from both the JSE and I-Net Bridge database (abbreviated as I-Net). In addition, accounting data (total assets, book value of equity, operating profit) is extracted from published financial statements downloaded from I-Net. In order to counter the effect of look-ahead bias, accounting data used in the study is collected by applying a three-month lag subsequent to the end of the financial year of the companies included in the sample, following studies such as van Rensburg (2001), Hodnett (2014), and Hsieh (2015). Total assets comprise of total current assets and total fixed assets (item termed "total assets" in financial statements obtained from I-Net). Book value of equity refers to common equity only and includes ordinary capital and reserves (item termed "equity"). Finally, operating profit is estimated following the definition of Fama and French (2015) and is computed as the difference between profit before interest and tax, and interest expense. The monthly closing prices and total return of ALSI are collected from I-Net. Meanwhile, the daily 91-day Treasury bill rates are collected from the South African Reserve

Bank (SARB) website; then monthly averages are computed for each month of the examination period. The ALSI index represents the market proxy while the South African 3-month Treasury bill yield is used as the risk-free rate of return, for the purpose of the study.

Before portfolios are formed, total returns of individual stocks are computed for each month, as the sum of capital gains and dividends for that particular month, using the below formula:

$$R_{it} = \frac{P_{it} - P_{it-1} + D_{it}}{P_{it-1}} \quad (4.1)$$

where

R_{it} is the return on stock i for month t

P_{it} is the closing price of the stock at the end of month t

P_{it-1} is the closing price of the stock at the end of month t-1 (the preceding month)

D_{it} is the estimated dividend paid at the end of month t, computed from the dividend yield for month t

When the total returns of individual stocks are obtained, the portfolio returns for each month are calculated as the arithmetic average of the total returns on the stocks included in the portfolio in question, following the formula below:

$$R_{Pt} = \sum_{i=1}^{N} R_{it}/N \quad (4.2)$$

where

R_{Pt} is the return on portfolio P for month t

R_{it} is the return on stock i for month t

N is the number of stocks included in the portfolio

The study minimises the potential effects of data snooping bias by extending the examination period to cover the latest financial information available on sample stocks and more recent macroeconomic information (as at 31 December 2018), which are less likely to have been incorporated in prior studies investigating market anomalies and multifactor asset pricing models on the JSE.

In a nutshell, collected data comprises of:

- Constituents of the ALSI from 1 January 2002 to 31 December 2018, which make up the research sample (after adjustments)
- Month-end closing prices for sample stocks
- Market capitalisation of companies included in the sample
- Book value of equity
- Total assets
- Operating profits
- Dividend yield
- South African 3-month Treasury bill rate
- ALSI monthly values

4.3 Research Methodology

Having reviewed the underlying rationale of the choice of the study period as well as the sources and types of data used for the study, this section proceeds with the specifications of the 3 main tests undertaken to achieve the objectives outlined in the introductory chapter. In effect, this section discusses the formation of style portfolios, the construction of asset pricing models, and the performance evaluation tools, implemented in each of the aforementioned tests. More specifically, the 3 tests involve the following:

- Tests on the existence of size, value, and momentum effects on the JSE
- Tests on the cyclicality of size, value, and momentum effects on the JSE
- Tests on the risk-based nature of size, value, and momentum effects

4.3.1 Tests on the Existence of Size, Value, and Momentum Effects on the JSE

In order to test the presence of size, value, and momentum effects on the JSE, as well as the explanatory power of the Fama-French three-factor model (henceforth FF3F), Carhart four-factor model (henceforth C4F), and Fama-French five-factor model (henceforth FF5F), a sorting procedure and time-series regression analysis are performed. However, before looking into the above, tests on the Capital Asset Pricing Model (CAPM) are performed first, as they set the benchmarks needed to assess the explanatory power of FF3F, C4F, and FF5F. Indeed, Fama and French (1992, 1993) build their three-factor model on the evidence from empirical studies that the CAPM is unable to explain the size effect and the value effect in the cross-section of stock returns. Carhart (1997) designs the four-factor model by augmenting FF3F with the momentum factor, while Fama and French (2015) add the profitability factor and the investment factor to their three-factor model to obtain the five-factor model.

4.3.1.1 CAPM Tests

Tests on the ability of the CAPM to capture variations in average portfolio returns on the JSE make use of a time-series regression of average portfolio returns on the market risk factor, as given by the below time-series regression equation:

$$R_{Pt} - R_{ft} = \alpha_P + \beta(R_{mt} - R_{ft}) + e_{Pt} \quad (4.3)$$

where

R_{Pt}	is the return on portfolio P in period t
R_{ft}	is the risk-free rate of return in period t, proxied by the 3-month South African Treasury bill yield
α_P	is the intercept of the regression, also known as Jensen's alpha, and represents abnormal return generated by portfolio P
β	is the beta of portfolio P, and represents the sensitivity of the returns on the portfolio to movements in the returns on the market portfolio
R_{mt}	is the return on the market portfolio in period t, the market portfolio being proxied by ALSI
$R_{mt} - R_{ft}$	is the market risk premium (MRP)
e_{Pt}	is the residual of the regression in period t

Monthly portfolio returns are regressed on the market risk factor proxied by $(R_{mt} - R_{ft})$ over the study period and the intercepts produced by the regressions are analysed, on the assumption that if systematic risk fully captures the variations in portfolio returns, then the intercepts of the regressions should not be different from zero, and should not be statistically significant (Fama and French, 1993). Otherwise, there are other risk factors driving the movements observed in average portfolio returns.

4.3.1.2 Factor Construction and Model Specification

Tests of the existence of size and value effects on the JSE, as well as the ability of FF3F to explain these effects, primarily follow the methodology of Fama and French (1993), with adjustments made where necessary to suit the South African context. The risk factors used as explanatory variables for the multifactor models are portfolios constructed based on the following sorting procedure.

The portfolios replicating the size and value factors are constructed using 2 x 3 independent sorts on size and book-to-market ratio (B/M). Stocks in the research sample are ranked based on their market capitalisation (market price multiplied by the number of common stocks outstanding) at the start of each year throughout the study period. Likewise, sample stocks are ranked based on their B/M at the start of each year. The B/M of each stock is computed as the book value of equity measured at the end of the last financial year of the company preceding the portfolio construction date, divided by the market value of equity recorded at the end of the calendar year preceding the portfolio construction date. The size-ranked sample is then broken down into 50th percentiles. Stocks falling in the lower 50% form the group termed Small (S) and those falling in the upper 50% form the group termed Big (B). Meanwhile, the B/M of the sample is broken down into 30th and 70th percentiles: low B/M (L), medium B/M (M) and high B/M (H).

This procedure results in six portfolios as size and B/M groups intersect, which are rebalanced on an annual basis at year end (S/H, S/M, S/L, B/H, B/M, and B/L). The size-related risk factor (SMB) is calculated monthly as the difference between the average of returns on the small-cap portfolios and the average of returns on the big-cap portfolios. In other words, SMB is the return on the factor portfolio which replicates the size effect in average returns. The value risk factor (HML) is computed monthly as the difference between the average of returns on the high B/M portfolios and the average of returns on the low B/M portfolios. More specifically:

$$SMB_{B/M} = \frac{(S/_L + S/_M + S/_H) - (B/_L + B/_M + B/_H)}{3} \quad (4.4)$$

$$HML = \frac{(S/_H + B/_H) - (S/_L + B/_L)}{2} \quad (4.5)$$

The procedure adopted above enables to compute the size factor independently from the value factor and vice versa, and therefore, mitigate the effect of one on the other (Fama and French, 1993).

The momentum factor is constructed using 2 x 3 independent sorts on size and momentum (Boamah, 2015; Fama and French, 2016). Stocks are ranked according to size following the procedure earlier described, with 50th percentile breakpoint. Then stocks are ranked at t-1 month end, and broken into 30th and 70th percentiles on the basis of their prior 11-month cumulative average returns (CAR). Momentum portfolios are rebalanced monthly. Winner stocks at the beginning of each month consists of top 30th percentile prior 11-month top performing stocks on average, while loser stocks at the start of each month consist of bottom 30th percentile prior 11-month least performing stocks on average. The momentum factor is, therefore, the difference between the average of the returns on the winner portfolios (W) and the returns on the loser portfolios (L), as is termed winners minus losers (WML). This sorting procedure produces 6 additional size portfolios (S/W, S/M, S/L, B/W, B/M, and B/L). Therefore, the SMB factor used in C4F is the average of the 2 SMB factors computed with sorts on B/M and MOM12.

$$WML = \frac{(S/_W + B/_W) - (S/_L + B/_L)}{2} \tag{4.6}$$

$$SMB_{MOM12} = \frac{(S/_L + S/_M + S/_W) - (B/_L + B/_M + B/_W)}{3} \tag{4.7}$$

$$SMB(C4F) = \frac{SMB_{B/M} + SMB_{MOM12}}{2} \tag{4.8}$$

The profitability and investment factors (robust minus weak - RMW and conservative minus aggressive - CMA respectively) are constructed following the methodology adopted by Fama and French (2015). The procedure is similar to the one for SMB and HML above since 2 x 3 independent sorts on size and operating profit (for RMW) and on size and investment (for CMA) are used. Operating profit at the start of the current year is calculated as the difference between revenue and the sum of cost of goods sold, interest expense and selling, general and administration expenses, all divided by the book value of equity, using accounting information as at the end of the previous financial year. Investment at the beginning of the current year is computed as the difference between total assets as at the end of the prior financial year and total assets as at the end of the year before the preceding one, all divided by total assets as at the end of the year before the preceding one.

The breakdown of operating profitability at 30% and 70% produces three groups: weak (W), medium (M), and robust (R). Similarly, the breakdown of asset growth produces three groups: conservative (C), medium (M), and aggressive (A). The returns on the portfolio replicating the profitability effect (robust minus weak - RMW) are computed as the difference between the average of the returns on the portfolios with robust operating profit and the average of the returns on the portfolios with weak operating profit. Meanwhile, the returns on the asset-growth-effect replicating portfolio (conservative minus aggressive - CMA) are obtained by subtracting the average of the returns on portfolios with aggressive asset growth policy from the average of the returns on portfolios with conservative asset growth policy.

The formation of the RMW and CMA factors results in 6 size-operating profit portfolios (S/R, S/M, S/W, B/R, B/M, and B/W) and 6 size-investment portfolios (S/C, S/M, S/A, B/C, B/M, and B/A). Consequently, the SMB factor used in FF5F is the average of the 3 SMB factors computed with sorts on B/M, operating profit (OP), and investment (Inv).

$$RMW = \frac{(S/R + B/R) - (S/W + B/W)}{2} \quad (4.9)$$

$$CMA = \frac{(S/C + B/C) - (S/A + B/A)}{2} \quad (4.10)$$

$$SMB_{OP} = \frac{(S/R + S/M + S/W) - (B/R + B/M + B/W)}{3} \quad (4.11)$$

$$SMB_{Inv} = \frac{(S/C + S/M + S/A) - (B/C + B/M + B/A)}{3} \quad (4.12)$$

$$SMB(FF5F) = \frac{SMB_{B/M} + SMB_{OP} + SMB_{Inv}}{3} \quad (4.13)$$

After the formation of factors designed to capture the size, value, and momentum (as well as profitability and asset growth) effects in average stock returns, the specification of the multifactor asset pricing models under investigation is laid out. More specifically, the FF3F, C4F and FF5F time-series regression equations are given by equations 4.14, 4.15, and 4.16 respectively as follows:

$$R_{Pt} - R_{ft} = \alpha_P + b_{mP}(R_{mt} - R_{ft}) + b_{sP}SMB_t + b_{vP}HML_t + e_{Pt} \quad (4.14)$$

$$R_{Pt} - R_{ft} = \alpha_P + b_{mP}(R_{mt} - R_{ft}) + b_{sP}SMB_t + b_{vP}HML_t + b_{wP}WML_t + e_{Pt} \quad (4.15)$$

$$R_{Pt} - R_{ft} = \alpha_P + b_{mP}(R_{mt} - R_{ft}) + b_{sP}SMB_t + b_{vP}HML_t + b_{rP}RMW_t + b_{cP}CMA_t + e_{Pt} \quad (4.16)$$

where

R_{Pt}	is the return on portfolio P in month t
R_{ft}	is the risk-free rate of return in month t
α_P	is the intercept of the regression, and represents the abnormal return generated by portfolio P
R_{mt}	is the return on the market portfolio in month t
SMB_t, HML_t, WML_t , RMW_t , and CMA_t	are returns on portfolios replicating the size, value, momentum, profitability and investment factors respectively
b_{mP} , b_{sP} , b_{vP} , b_{wP} , b_{rP} and b_{cP}	are factor loadings on the market, size, value, momentum, profitability, and investment factors respectively; they represent the sensitivity of portfolio returns to variations in the aforementioned style premiums
e_{Pt}	is the residual of the regression in month t

4.3.1.3 Construction of Test Portfolios

Subsequent to the construction of factors to be used as explanatory variables, portfolios whose returns are to be explained (dependent variables, termed test portfolios) are equally constructed, still following a procedure similar to Fama and French (1993). More specifically, nine portfolios are formed from 3 x 3 independent sorts on size and B/M, with the breakpoints standing at the 30^{th} and 70^{th} percentiles of the stock sample as earlier specified. Fama and French (1993) use 5 x 5 sorts on size and B/M to form 25 portfolios; however, Boamah (2015) argues that as the South African stock market is much smaller than the U.S. stock market, a 3 x 3 independent sorting procedure is more appropriate in the context of the JSE. Equally, nine additional portfolios are constructed using 3 x 3 sorts on size and momentum. The excess returns (returns in excess of the risk-free rate) on the 18 portfolios formed over the study period represent the dependent variables in the regression equations.

In order to test the existence of the size, value, and momentum effects on the JSE over the examination period and sub-periods specified earlier, the monthly excess average returns on the 18 portfolios formed above are analysed. If the excess returns on the size portfolios decrease from the small-size to the big-size group in B/M segments and MOM12 segments, this indicates an inverse relationship between size and return and, consequently, the existence of the size effect on the JSE over the study period. Similarly, the tests provide evidence of the value effect on the JSE if the excess returns on B/M portfolios increase from bottom B/M group (growth stocks) to top B/M group (value stocks) in size segments. Lastly, an increase in average excess returns on MOM12 portfolios from bottom to top MOM12 30^{th} percentiles indicates the existence of the momentum effect on the JSE over the study period. This analysis is performed both over the whole examination period and sub-periods.

4.3.1.4 Performance Attribution of Returns on Test Portfolios

Tests on the ability of FF3F, C4F, and FF5F to explain stock returns on the JSE over the examination period focus on the coefficient of determination (R^2 and adjusted R^2), the intercept (α) and slopes (factor loadings) obtained from the time-series regressions (using equations 4.14, 4.15, and 4.16 above) of portfolio returns on factors constructed earlier.

The adjusted R^2 informs on whether the additional SMB and HML are redundant in the case of FF3F. With respect to C4F, it indicates whether SMB, HML, and WML are redundant. In the case of FF5F, it provides insight on any multicollinearity issue that may exist between the explanatory factors on the JSE. Indeed, Fama and French (2015) report that the explanatory power of the value factor weakens in their five-factor model on the U.S. market, and a similar outcome is uncovered by Mahlophe (2015) on the JSE. However, Chiah, Chai, Zhong, and Li (2016) in Australia, and Jiao and Lilti (2017) in China, reveal contradictory findings as they show that the value risk factor maintains its strong explanatory power in FF5F.

The magnitude and statistical significance of α inform on the explanatory power of the multifactor asset pricing models under investigation. In effect, Fama and French (1993) assert that if an asset pricing model does a good job in explaining asset returns, then the regression intercept (the abnormal return generated by the asset) should not differ from zero.

With respect to factor loadings, their magnitude and statistical significance provide indication on the drivers of stock performance on the JSE over the study period.

4.3.2 Tests on the Cyclicality of Size, Value, and Momentum Effects on the JSE

The cyclical behaviour of the style effects under investigation is examined with a view to establishing whether they are pervasive on the South African stock market throughout the study period. The tests equally purport to determine whether variations in size, value, and momentum premiums are positively or negatively correlated with the South African business cycle; that is, if they are procyclical or countercyclical.

In order to achieve these objectives, a performance evaluation of SMB, HML, and WML factor portfolios constructed earlier is carried out over the whole study period and specific sub-periods, reflecting upward and downward phases of the South African business cycle. Indeed, the returns on SMB, HML, and WML factor portfolios reflect the size risk premium, value risk premium, and momentum risk premium respectively, which are embedded in stock returns on the JSE.

The performance evaluation tools used in these tests include the mean, the standard deviation, and the Sharpe ratio of the returns on SMB, HML, and WML factor portfolios. The monthly returns are obtained using a formula similar to Equation 4.2 above:

$$r_{Pt} = \sum_{i=1}^{N} r_{it}/N \qquad (4.17)$$

where

r_{Pt} is the return on factor portfolio P for month t

r_{it} is the return on stock i for month t

N is the number of stocks included in the portfolio

Then, the mean return R_P is computed as the arithmetic average of the monthly returns, for the full study period and for the sub-periods specified earlier.

The standard deviation of the mean return on factor portfolios is equally calculated as follows:

$$\sigma_P = \sqrt{\frac{\sum_{t=1}^{n}(r_{Pt} - R_P)^2}{n}} \qquad (4.18)$$

where

σ_P is the standard deviation for the factor portfolio P, reflecting the risk embedded in the portfolio

r_{Pt} is the return on factor portfolio P for month t

R_P is the mean return on factor portfolio P

n is the number of months in the period or sub-period

Lastly, the Sharpe ratio is given by:

$$Sharpe\ ratio = \frac{R_P - R_f}{\sigma_P} \qquad (4.19)$$

where R_f is the risk-free rate of return.

The Sharpe ratio is a relevant performance evaluation tool in this context as it assesses the performance of factor portfolios on a risk-adjusted basis and, therefore, provides unique insights in the magnitude of the risk premiums generated by the style portfolios per unit of total risk over the examination period and over the sub-periods corresponding to the various phases of the business cycle.

The above performance evaluation measures are equally calculated for the ALSI, which represents the market proxy for the purpose of the study and the benchmark for the comparison of the performance measures for the factor portfolios. These tools have been adopted in earlier international and South African studies and, thus, set a meaningful comparative ground for the findings of this study (see for example Hsieh, 2015; and Fama and French, 2016).

In addition to the above analyses, the monthly returns of SMB, HML, and WML factor portfolios are graphically represented as a function of time in order to display the trends of, and variations in, the style risk premiums over the study period and sub-periods.

The examination period embodies 2 upward phases and 2 downward phases of the business cycles, as identified by the SARB in its September 2018 quarterly bulletin: January 2002 – November 2007, and September 2009 – November 2013 for the upward phases, and December 2007 – August 2009, and December 2013 - December 2018, for the downward phases.

If the size, value, and momentum premiums (proxied by returns on SMB, HML, and WML factor portfolios) experience significant fluctuations over the various phases of the South African business cycle, then the style premiums are cyclical. Moreover, the style premiums are procyclical if they increase in upward phases and decrease in downward phases of the business cycle. However, if they rise in downward phases and fall in upward phases, then they are countercyclical.

4.3.3 Tests on the Risk-Based Nature of Size, Value, and Momentum Effects

Tests in this section are meant primarily to determine if size, value, and momentum premiums are driven by risk. It is worth noting here that the purpose of these tests is not to investigate the specific type(s) of risk that induce(s) the style premiums. Rather, the objective is to determine whether the style premiums can be attributed to risk. In addition, the tests equally investigate whether small-cap, high B/M, and prior-winner portfolios, are riskier than their respective counterparts, namely big-cap, low B/M, and prior-loser portfolios.

Prior studies, as reviewed in Chapter 3, have put forth several risk-based explanations with regard to the existence of size, value, and momentum premiums. Some of those explanations include macroeconomic risks, credit risk, volatility risk, and crash risk, just to name a few (see for instance Fama and French, 1993, 1995; Liew and Vassalou, 2000; Chordia and Shivakumar, 2002; Hwang, Min, McDonald, Kim, and Kim, 2010; Avramov, Chordia, Jostova, and Philipov, 2013; Peltomäki and Äijö, 2015; Daniel and Moskowitz, 2016; and Ruenzi and Weigert, 2018). Besides, Ross (1976), in designing the Arbitrage Pricing Theory (APT), asserts that systematic risk (also known as market risk) can be broken down into several risks associated with macroeconomic components. Meanwhile, Fama and French (1993) show that although the market risk premium leaves unexplained a significant part of variations in stock returns, it does, however, capture a large portion of these common movements. More interesting, the market risk premium is positively correlated to the size risk premium (correlation coefficient of 0.32) and negatively correlated to the value risk premium (correlation coefficient of - 0.38).

Following the above observations, tests pertaining to the risk-base rationale of size, value, and momentum effects make use of beta (β) as the measure of risk. In the context of this study, beta measures the sensitivity of returns on SMB, HML, and WML factor portfolios to variations in the returns on the market portfolio (proxied by ALSI). In other words, beta measures the market risk, or volatility, embedded in the style premiums.

Beta is obtained through a time-series regression of the average monthly returns on the factor portfolios on the market risk factor, using the CAPM regression equation outlined in equation 4.3:

$$R_{Pt} - R_{ft} = \alpha_P + \beta(R_{mt} - R_{ft}) + e_{Pt} \quad (4.20)$$

where R_{Pt} is the return on the portfolio P for period t, R_{ft} is the risk-free rate of return in period t, α_P (Jensen's alpha) is the intercept of the regression, β is the beta of the portfolio, R_{mt} is the return on the market portfolio in month t, $R_{mt} - R_{ft}$ is the market risk premium, and e_{Pt} is the residual of the regression in month t.

The betas of size, value, and momentum premiums are reported for the full study period and for the sub-periods comprised in the study period, and their variations are analysed in light of the major economic trends identified in the various sub-periods in question (expansions, recessions, and crisis). Here, the coefficient of determination (R^2) informs on the proportion of the variations in the factor premiums explained by the market risk factor, while beta reflects the movements in the factor premiums in relation to movements in the returns on the market portfolio. An increase in R^2 values and betas (reflecting higher exposure of factor premiums to systematic risk) in periods of high market volatility (recession and crisis), coupled with a fall in R^2 values and betas (reflecting lower exposure of factor premiums to systematic risk) during low market volatility periods (expansion) is indicative of the risk-based nature of the aforementioned style effects as the movements inform on the volatility (riskiness) of factor premiums in relation to market conditions.

In order to investigate whether small stocks, value stocks, and winner stocks are riskier than their respective big, growth, and loser counterparts, the tests further estimate the betas of 6 style portfolios over the different phases of the South African business cycle identified throughout the examination period. The 6 portfolios include: small-cap, large-cap, value, growth, winner, and loser portfolios. The small-cap portfolio is made up of the bottom 50% stocks ranked by market capitalisation at the beginning of each year, following the procedure described earlier in constructing factor portfolios. Conversely, the top 50% size-ranked stocks constitute the large-cap portfolio. Similarly, top 30% B/M stocks form the value portfolio, while the bottom 30% B/M stocks form the growth portfolio. Lastly, winner portfolios comprise of top 30% MOM12 stocks whereas loser portfolios include the bottom 30% MOM12 stocks.

Beta is calculated by dividing the covariance of the average monthly returns on each style portfolio and the average monthly returns on the market portfolio, by the variance of the returns on the market portfolio, as follows:

$$\beta_P = \frac{covar\ (R_P, R_m)}{var\ (R_m)} \qquad (4.21)$$

β_P is the beta of style portfolio P

R_P is the mean return on style portfolio P

R_m is the return on the market portfolio

$covar$ denotes the covariance

var denotes the variance

The Treynor measure is equally computed for the 6 style portfolios mentioned above in order to evaluate how well the investment styles fare when adjusted for market risk, over the entire examination period and the various phases of the business cycle.

The Treynor measure is given by:

$$Treynor\ measure = \frac{R_P - R_f}{\beta_P} \qquad (4.22)$$

where

R_P is the mean return on style portfolio P

R_f is the risk-free rate

β_P is the beta of style portfolio P

The betas of the small-cap, value, and winner portfolios are compared to those of their respective large-cap, growth, and loser counterparts over the examination period and sub-periods. If the beta of the small cap portfolio is higher than that of large cap portfolios, then small caps are more volatile than large caps and, consequently, riskier. Likewise, if the beta of value (winner) portfolios is higher than that of growth (loser) portfolios, then value (winner) stocks are riskier than growth (loser) stocks.

4.4 Research Biases and Possible Remedies

The research biases likely to affect the results of the study have been identified and include survivorship bias, look-ahead bias, and data snooping bias. They are presented below, as well as the steps taken to mitigate their effects on the study.

4.4.1 Survivorship Bias

The I-Net Bridge database is subject to survivorship bias given that some stocks included in the database ceased to trade or were delisted in the course of the study period. This might lead to skewed results towards the stocks that have survived over the period, and result in invalid inferences if the dataset used in the study is not adjusted accordingly. To control for survivorship bias, the stocks that have been suspended or unquoted in the research sample are included in the latter until the date they cease to be traded. After this date, those stocks are removed from the sample for the remainder of the examination period. However, as the study sample consists of common stocks included in the ALSI over the period 2002 – 2018, the findings might be subject to thin trading as some small stocks included in the sample might not trade frequently. In this regard, the thin trading adjustment in similar studies would be interesting for further research.

4.4.2 Look-Ahead Bias

The study sample is equally subject to look-ahead bias as the accounting data used is collected from published end-of-year financial statements. Actually, companies listed on the JSE have a maximum period of 3 months subsequent to the end of their financial year to publish their financial statements (JSE Limited, 2018). This implies that accounting data required for the study (for example book value of equity, total assets, etc.) is not available right after the end of the year. The study therefore remedies the effect of look-ahead bias on the research sample by allowing for a 3-month time lag between the end of the financial year of companies present in the sample and the time their accounting data is collected for the purpose of the research.

The 3-month time lag has been employed by prior South African studies such as van Rensburg (2001), Hodnett (2014), and Hsieh (2015), among others. Consequently, adopting this procedure enables meaningful comparison of findings with previous studies.

4.4.3 Data Snooping Bias

The review of South African literature on asset pricing and market anomalies undertaken earlier revealed that a significant amount of research has been carried out with regard to the existence of size, value, and momentum anomalies, along with the ability of multifactor models to capture those effects in stock returns on the JSE. Consequently, to minimise the likelihood of data snooping bias affecting the results of this study, the examination period has been extended to include the latest market and company information available at the time of writing. Indeed, the study covers the period from 1 January 2002 to 31 December 2018 and, therefore, incorporates the events which led to the recent technical recession episode experienced by the South African economy in the third quarter of 2018. More important, the data used in this study is a fresh dataset compared to prior international studies and, consequently, constitutes out-of-sample data which adds to the independence and relevance of the study's findings.

4.5 Conclusion

This chapter provides the details of the procedure undertaken to collect data and carry out the tests necessary to achieve the objectives of the study, as laid out in the introductory chapter. At first, the chapter defines the examination period (1 January 2002 – 31 December 2018) and relevant sub-periods, and explains the motivation behind this choice. Then, the research sample, sources, and types of data are presented, along with the adjustments made to the data to suit the purpose of the study.

Next, the tests included in the methodology are thoroughly reviewed. More specifically, tests on the existence of size, value, and momentum effects are carried out using a portfolio sorting procedure. The procedure results in the construction of size, value, and momentum factor portfolios, termed small-minus-big (SMB), high-minus-low (HML), and winner-minus-loser (WML). 18 tests portfolios are equally constructed, including 9 portfolios on size and B/M, and 9 portfolios on size and MOM12. The trends in the average monthly returns in the various style segments are analysed over the various sub-periods in order to uncover the presence of these anomalies on the JSE. The ability of multifactor models to capture these effects is investigated using the Fama-French three-factor model, Carhart four-factor model, and Fama-French five-factor model. Indeed, a time-series regression of the returns on the 18 test portfolios on the returns on factor portfolios is performed for each of the asset pricing models mentioned above over the study period.

Besides, the cyclical behaviour of size, value, and momentum premiums is evaluated using performance measures including the mean, the standard deviation, and the Sharpe ratio, while the risk-based rationale of these style premiums is tested by computing and comparing their betas. In addition, the risk-relationship between small caps and large caps, value and growth stocks, and winners and losers, is analysed using beta and the Treynor measure.

At last, the chapter highlights the research biases the study is exposed to and which are likely to tamper with the validity of the results, namely survivorship bias, look-ahead bias, and data snooping bias, and explains the steps that have been undertaken to reduce the impact of the biases on the findings.

CHAPTER 5 – EXISTENCE OF SIZE, VALUE, AND MOMENTUM EFFECTS ON THE JSE

5.1 Introduction

The purpose of this chapter is to present and discuss the findings pertaining to the existence of size, value, and momentum effects on the Johannesburg Stock Exchange (JSE) over the period from 1 January 2002 to 31 December 2018. In addition, it discusses the results of the tests related to the suitability of selected asset pricing models to capture these anomalies in average stock returns on the JSE. The models under investigation include: the Capital Asset Pricing Model (CAPM), the Fama-French three-factor model (FF3F), the Carhart four-factor model (C4F), and the Fama-French five-factor model (FF5F).

In this regard, the results of two main sets of tests are displayed and analysed. The first set of results, discussed in Section 5.3, presents the mean monthly returns of 18 style-based portfolios formed on size and book-to-market ratio (B/M) (9 portfolios), and size and prior 12-month returns (MOM12) (9 portfolios). The monthly returns are analysed in order to determine whether peculiar patterns emerge, namely size effect (small-cap portfolios outperforming large-cap portfolios), value effect (high B/M portfolios outperforming low B/M), and momentum effect (high past 12-month-returns portfolios outperforming low past 12-month-returns portfolios). The analysis is undertaken over the full examination period (2002 - 2018), and also over specific sub-periods: two upward periods (2002 – 2007 and 2009 - 2013) and two downward periods (2007 – 2009, and 2013 - 2018).

The second set of results, discussed in Section 5.4, highlights the outcome of the times-series regressions of the excess returns on the 18 portfolios mentioned above on the factors of the CAPM, FF3F, C4F, and FF5F over the study period. The performance of the asset pricing models in explaining the size, value, and momentum effects is assessed through the analysis of the coefficient of determination (r-squared) and the intercept of the regression (which represents the abnormal return generated by the style portfolios). Moreover, the factors driving the returns on style portfolios under investigation on the South African stock market are evaluated through the analysis of the slope(s) of the regressions (loadings on factors included in the models). Finally, FF3F and FF5F are compared in terms of their explanatory power as Fama and French (2015) claim that the latter exhibits a stronger explanatory power than the former.

5.2 Chapter Objectives

As previously discussed in Chapter 3 (Sections 3.2 and 3.3), most empirical evidence documents the presence of size, value, and momentum effects on capital markets (for example Basu, 1977; Banz, 1981; and Jegadeesh and Titman, 1993), though a few studies contend that these effects have attenuated or disappeared over the years (for instance Fraser, 1995; Schwert, 2003; and Hwang and Rubesam, 2008). In addition, the asset pricing models designed to capture the aforementioned style effects in average stock returns have been found to do the job very well on international markets and on the JSE (for example Fama and French, 1993; Carhart, 1997; and Basiewicz and Auret, 2010). However, few prior studies document the inability of the models to explain the anomalies, such as Halliwell, Heaney, and Sawicki (1999), Chen and Fang (2009), and Boamah (2015).

In this regard, the main objective of this chapter is twofold:

- To investigate the existence of the size, value, and momentum effects on the JSE over the period from 1 January 2002 to 31 December 2018;
- To assess whether the CAPM, the FF3F, the C4F, and the FF5F explain those effects in the cross-section of stock returns on the JSE over the aforementioned period.

5.3 Evidence of Size, Value, and Momentum on the JSE

The existence of size, value, and momentum effects is investigated over the study period as a whole, and over sub-periods specified earlier, which represent the upward and downward phases of the South African business cycle identified in the examination period. The sub-period investigation is performed owing to a few prior studies arguing that these effects tend to vanish or attenuate after they have been observed (see for example Schwert, 2003, in the U.S.; and Auret and Cline, 2011, in South Africa).

5.3.1 Full Period

Table 5.1 below displays the average monthly excess returns on the 18 style portfolios formed on size and B/M, and size and MOM12 (see Chapter 4, sub-section 3.1.3), over the period from 1 January 2002 to 31 December 2018.

Table 5.1 : Average Monthly Excess Returns on Test Portfolios for the Period 2002-2018

		Panel A: B/M				Panel B: MOM12			
		Low	Medium	High	High-Low	Loser	Medium	Winner	Winner-Loser
Size	Small	0.0487	0.0449	0.0419	-0.0068	0.0184	0.0594	0.0779	0.0595
	Medium	0.0391	0.0388	0.0435	0.0044	0.0169	0.0395	0.0691	0.0522
	Big	0.0362	0.0350	0.0365	0.0003	0.0196	0.0366	0.0529	0.0333
	Small-Big	0.0125	0.0099	0.0055		-0.0012	0.0228	0.0250	

Panel A of Table 5.1 above presents the mean monthly excess returns on the 9 portfolios formed on size and B/M for the full study period. For every B/M group, the average excess returns decrease from small-cap portfolios to large-cap portfolios, thereby showing evidence of the size effect on the JSE. Except for the high B/M group, the decrease is monotonic. With regard to the trend in returns on B/M portfolios, the Table shows that average monthly excess returns increase from low B/M to high B/M portfolios in both medium caps and large caps, hence evidence of the value effect.

However, the returns rather decrease in the small-cap group, resulting in a negative 0.68% monthly return differential over the study period. This result contradicts the evidence by Fama and French that the B/M effect tends to be stronger in small caps (Fama and French, 1993, 2015). Nevertheless, the result aligns with Hammar (2014) and Hsieh (2015) who both find that value stocks underperform growth stocks when portfolios are formed on price-to-book ratio (P/B) and book-to-price ratio (B/P), respectively. This may mean that investors on the JSE find small companies which experience rapid growth to be more attractive that small companies which exhibit low-growth potential, at least over the study period. The evidence of the size effect and value effect on the South African stock market corroborates the findings by Fama and French (1992, 1993) and Asness, Frazzini, Israel, Moskowitz, and Pedersen (2018) in the U.S., Annaert, Crombez, Spinel, and Van Holle (2002), and Desban and Jajir (2016) in other international markets, Basiewicz and Auret (2009), and Hsieh (2015) for the size effect, and Page and Auret (2018) for the value effect, on the JSE, among others.

Panel B of Table 5.1 displays the average excess returns per month on the 9 style portfolios formed on size and MOM12, over the whole examination period. Panel B provides further evidence of the size effect on the JSE as the average returns fall (though non-monotonically) from small-cap portfolios to large-cap portfolios in the medium and high (winner portfolios) MOM12 groups. However, the size effect is not observed in the low MOM12 group (loser portfolio) as the return differential between small caps and large caps is negative (-0.12%).

The analysis of the average monthly excess returns on momentum portfolios exhibited in Table 5.1 reveals a consistent surge in returns from loser portfolios to winner portfolios in all size groups, with return differentials ranging between 3% and 6%. These results provide clear evidence of the momentum effect on the JSE, and echo the findings by prior studies on both international and South African stock markets (see for instance Jegadeesh and Titman, 1993; Rouwenhorst, 1998; Jegadeesh and Titman, 2001; Fama and French, 2012; Hoffman, 2012; Page and Auret, 2017, 2018; and Zaremba, 2018).

Having established the presence of size, value, and momentum effects on the JSE over the full study period, this study then investigates the existence of these effects over the upward phases and downward phases of the economic cycle identified over the examination period.

5.3.2 Upward Periods (2002-2007 and 2009-2013)

Table 5.2 exhibits the mean monthly excess returns on the 18 style portfolios constructed on size and B/M, and size and MOM12, over the 2 upward phases of the South African business cycle embedded in the examination period. Panel A summarises the results for the first upward phase (January 2002 - November 2007), while Panel B summarises the results for the second one (September 2009 – November 2013).

Table 5.2 : Average Monthly Excess Returns on Test Portfolios for the Period 2002-2007 (Panel A) and 2009-2013 (Panel B)

Panel A (2002-2007)		Panel A1: B/M				Panel A2: MOM12			
		Low	Medium	High	High-Low	Loser	Medium	Winner	Winner-Loser
Size	Small	0.0698	0.0647	0.0736	0.0038	0.0406	0.0987	0.1011	0.0605
	Medium	0.0536	0.0546	0.0519	-0.0017	0.0263	0.0514	0.0878	0.0616
	Big	0.0411	0.0449	0.0503	0.0092	0.0310	0.0442	0.0673	0.0362
	Small-Big	0.0287	0.0198	0.0233		0.0096	0.0545	0.0338	
Panel B (2009-2013)		Panel B1: B/M				Panel B2: MOM12			
Size	Small	0.0641	0.0419	0.0284	-0.0357	0.0168	0.0451	0.0694	0.0526
	Medium	0.0454	0.0389	0.0359	-0.0096	0.0128	0.0363	0.0658	0.0530
	Big	0.0457	0.0457	0.0271	-0.0186	0.0091	0.0398	0.0554	0.0463
	Small-Big	0.0184	-0.0038	0.0013		0.0077	0.0053	0.0140	

5.3.2.1 Upward Period 2002 - 2007

Panel A1 of Table 5.2 shows that the average monthly excess returns on the 9 style portfolios diminish from small-cap portfolios to large-cap portfolios in a monotonic trend across all B/M groups over the period from 2002 to 2007. More interesting, the excess returns on all the 9 portfolios are higher than their respective excess returns presented earlier in Panel A of Table 5.1, resulting in higher return differential. Indeed, while the highest return differential between small-cap and large-cap portfolios stands at 1.25% per month in Panel A of Table 5.1 for B/M groups, the lowest differential in Panel A1 of Table 5.2 amounts to 1.98% per month. In other words, the size effect is stronger on The JSE during the first upward period as compared to the full period. These findings disagree with Auret and Cline's (2011) who find that there is no size effect on the JSE over the period 1988 – 2006. This disagreement may be caused by the difference in examination periods, as Auret and Cline's (2011) include the JSE restructuring period and the internet bubble burst period.

With respect to B/M portfolios, Panel A1 of Table 5.2 reveals that mean monthly excess returns rise from low B/M portfolios (growth stocks) to high B/M portfolios (value stocks) in small-cap and large-cap groups, which is evidence of the value effect over the sub-period.

However, in the mid-cap group, the value effect is non-existent as the difference between the average returns on growth-stock portfolios and value-stock portfolios stands at -0.17%. This may imply that during the period 2002-2007, investors favoured value stocks over growth stocks found at the extreme ends of the size spectrum, but preferred growth stocks over value stocks in the middle of the spectrum. As observed with the size-based portfolios, the value-growth differential tends to be larger (except for mid-cap portfolios) in Panel A1 of Table 5.2 (2002-2007 period) than in Panel A of Table 5.1 (2002-2018 period).

Panel A2 of Table 5.2 shows the mean monthly excess returns on the 9 portfolios constructed on size and MOM12 for the upward phase of the business cycle starting in January 2002 and ending in November 2007. The analysis of the returns confirms the presence of the size effect on the JSE over that period, as returns fall from small caps to large caps in all MOM12 groups. Similar to the observation in Panel A1, the monthly returns on portfolios in Panel A2 are higher than in Panel B of Table 5.1, confirming the stronger size effect observed in Panel A1 of Table 5.2.

The returns on momentum portfolios experience a monotonic increase from loser groups to winner groups in all size segments. In other words, the momentum effect is observed on the JSE over the 2002-2007 period. In addition, the effect is stronger during this period than over the full period, as demonstrated by higher return differentials in Panel A2 of Table 5.2 in comparison to those in Panel B of Table 5.1. More interesting, differences in average returns for MOM12 groups are higher than those for size and B/M groups, which may signify that during the upward period, the momentum investment style yielded higher returns than size and value investment styles. This supports the evidence by Muller and Ward (2013) that the momentum style outperformed size and value styles (among other styles) on the JSE over the period 1985-2011.

The superior performance of style portfolios during the period 2002-2007 as compared to the full examination period is probably due to the fact that the aforementioned period witnessed an economic boom for the South African economy, with the average annual growth in GDP exceeding 3% over the period in question (World Bank, 2019). This economic expansion, therefore, favoured impressive performance of style portfolios under investigation.

5.3.2.2 Upward Period 2009 - 2013

The analysis of Panel B1 of Table 5.2 uncovers the size effect in low and high-B/M groups, as average monthly excess returns decline from small-cap portfolios to large-cap portfolios in the 2 B/M groups mentioned above. The medium B/M group, however, experiences a reversal of the size effect, resulting in a monthly return differential between small caps and large caps of -0.38%. Interestingly, the small-big return differentials are much lower in Panel B1 than in Panel A1 of Table 5.2. In effect, the lowest return differential in Panel A1 stands at 1.98% whereas the highest return differential in Panel B1 is 1.84%. These results may not be surprising given that the 2009-2013 period witnessed the aftermath of the 2008 financial crisis and was, consequently, more of a recovery period for the South African economy (and the global economy as well). In this regard, the period inherited the fallout of the financial crisis, leading to lower performance on the stock market as compared to pre-crisis performance levels.

The lower performance of the stock market during the period 2009-2013 is more visible through the analysis of average monthly excess returns on B/M portfolios displayed in Panel B1 of Table 5.2. Indeed, the average returns decline from low B/M to high B/M portfolios, resulting in a negative value-growth differential in every size group. In other words, value stocks underperformed growth stocks in the 2009-2013 upward phase of the South African business cycle. Consequently, the value effect is not observed on the JSE over that period.

Panel B2 of Table 5.2 adds to the evidence of the existence of the size effect on the South African stock market during the period from 2009 to 2013. The analysis of the mean monthly returns of the 9 portfolios formed on size and MOM12 uncovers a negative relationship between size and average returns, as the returns fall from small caps to large caps in each MOM12 segment. Nevertheless, as noted earlier in Panel B1, the returns are much lower than the returns generated during the first upward period presented in Panel A2 of Table 5.2.

The momentum returns displayed in Panel B2 of Table 5.2 rise progressively from loser portfolios to winner portfolios across all size groups, providing evidence of the existence of the momentum effect on the JSE during the period 2009-2013. However, the effect is weaker than during the 2002-2007 period, except for the large-cap segment, where the MOM12 return differential equals to 4.63% per month for the second upward period, which is greater than 3.62% monthly differential reported in the first upward period. These findings may imply that momentum portfolios formed on large caps may perform better in the aftermath of a financial crisis.

5.3.3 Downward Periods (2007-2009 and 2013-2018)

Table 5.3 summarises the average monthly excess returns on the 18 style portfolios formed on size and B/M, and size and MOM12, over the 2 downward phases of the South African economic cycle identified in the study period under examination. Panel A is comprised of the results for the first downward phase (December 2007 - August 2009, which actually encompasses the 2008 global financial crisis), while Panel B is comprised of the results for the second downward phase (December 2013 – December 2018).

Table 5.3 : **Average Monthly Excess Returns on Test Portfolios for the Period 2007-2009 (Panel A) and 2013-2018 (Panel B)**

Panel A (2007-2009)		Panel A1: B/M				Panel A2: MOM12			
		Low	Medium	High	High-Low	Loser	Medium	Winner	Winner-Loser
Size	Small	0.0007	0.0064	0.0090	0.0083	-0.0105	0.0236	0.0614	0.0719
	Medium	0.0166	0.0180	0.0465	0.0299	0.0169	0.0290	0.0530	0.0361
	Big	0.0272	0.0145	0.0341	0.0069	0.0207	0.0235	0.0331	0.0124
	Small-Big	-0.0265	-0.0081	-0.0251		-0.0312	0.0002	0.0283	
Panel B (2013-2018)		Panel B1: B/M				Panel B2: MOM12			
Size	Small	0.0278	0.0377	0.0278	0.0000	0.0039	0.0378	0.0637	0.0598
	Medium	0.0248	0.0274	0.0392	0.0144	0.0094	0.0318	0.0557	0.0463
	Big	0.0257	0.0319	0.0291	0.0034	0.0147	0.0295	0.0408	0.0261
	Small-Big	0.0021	0.0058	-0.0013		-0.0108	0.0083	0.0228	

5.3.3.1 Downward Period 2007-2009

According to Panel A1 of Table 5.3, monthly excess returns on the 9 portfolios built on size and B/M increase from small-cap portfolios to large-cap portfolios, over the period 2007-2009. This means that small caps underperform large caps on the JSE over the specified period, causing a reversal of the size effect. In other words, the size effect vanishes during the

2007-2009 period on the South African stock market. This result aligns with findings from a few prior studies which assert that small caps do not consistently perform better than large caps over time. Examples include Horowitz, Loughran, and Savin (2000) and Schwert (2003) in the U.S., as well as Auret and Cline (2011), Hammar (2014), and Page, Britten, and Auret (2016) in South Africa. The poor performance of small caps over large caps may be attributed to the uncertain market conditions prevailing during the period, caused by the 2008 global financial crisis, which led investors to shy away from the stock market.

Turning to returns on B/M portfolios, Panel A1 of Table 5.3 reveals that the value effect is present across the whole size spectrum during the 2007-2009 period. Indeed, average monthly excess returns increase from low B/M portfolios (growth stocks) to high B/M portfolios (value stocks) in each size group. Unlike the upward phases during which the value effect was observed in only two size segments out of three, the value effect is observed in this downward period in all size segments. This observation concurs with the results of Barnard and Bunting (2015) who demonstrate that the value effect is prevalent on the JSE during the market downturn surrounding the 2008 global financial crisis period. This may imply that value stocks perform better than growth stocks irrespective of the size of the company, during turbulent economic times.

The examination of Panel A2 of Table 5.3 brings to light the reversal of the size effect in the loser segment (return differential of -3.12% per month), and a weak size effect in the medium MOM12 segment (return differential of 0.02% per month). However, the size effect is present in the winner segment, with the differential standing at 2.83% per month. A possible explanation is that small companies who have performed well in the past 12 months are more resilient during poor economic conditions than their large counterparts. The analysis of momentum portfolios shows that the momentum effect remains relatively strong during the 2007-2009 period, given that average monthly excess returns rise monotonically from loser to winner portfolios in all size groups, with the lowest monthly return differential amounting to 1.24%. However, the performance levels of momentum portfolios are lower on average, compared to their levels in both upward periods presented in Table 5.2 (Panels A2 and B2) above.

5.3.3.2 Downward Period 2013-2018

Panel B1 of Table 5.3 displays a downward trend in average excess returns from small caps to large caps in low and medium B/M groups, but a rather upward trend in the high B/M group.

In other words, the size effect is prevalent in low and medium B/M segments, but not in the high B/M segment, over the period 2013-2018. However, the returns stand at a higher level than the levels observed during the period 2007-2009. This illustrates the fact that the 2013-2018 downward period is subject to much less harsh business conditions than during the 2007-2009 financial crisis period. Nevertheless, the performance of small and large caps remains well below their pre-2007 level. These findings support Page, Britten, and Auret's (2016) findings that the size effect has declined significantly on the JSE over the period from 1992 to 2014.

Looking at B/M portfolios in Panel B1 of Table 5.3, mean monthly excess returns increase from low-stock portfolios (low groups) to value-stock portfolios (high groups) in medium- and big-cap segments during the period 2013-2018. In the small-cap group, the monthly return of low and high B/M groups stand at the same level, delivering a differential of 0%. Surprisingly, the return differentials between value- and growth-stock portfolios are smaller than the differentials reported during the 2007-2009 period, although the latter experienced more volatile market conditions due to the financial crisis. The inference may be that value stocks may perform at optimum levels during crisis periods or, more generally, during periods of highly turbulent economic conditions.

According to Panel B2 of Table 5.3, the 9 portfolios formed on size and MOM12 exhibit a performance similar to that of the 2007-2009 period. More specifically, a reversal of the size effect is noticed in the loser group (return differential of -1.08%), though the effect is weaker than in the first downward period. Besides, the size effect is observed in the medium and winner segments of MOM12 portfolios, with similar performance levels in the latter segment. This result tends to support the earlier observation that small caps with good prior 12-month performance tend to outperform their large counterparts. Again, the momentum effect is uncovered as mean monthly excess returns increase steadily from low MOM12 portfolios (losers) to high MOM12 portfolios (winners) in every size segment. Lastly, the returns levels look similar to the ones reported in 2007-2009, and are lower than those observed in upward periods.

The above analysis of average monthly excess returns on style portfolios puts forth the existence of size, value, and momentum effects on the JSE over the period from 2002 to 2018, even though the sub-period examination reveals variations in the magnitude of each of these style effects. Consequently, the above results are consistent with the findings by most previous studies on international and South African stock markets, such as Basu (1977), Banz (1981), Fama and French (1992,1993), Jegadeesh and Titman (1993), van Rensburg (2001), Basiewicz and Auret (2009), and Hoffman (2012), to name but a few. The next step of this study is to investigate whether the aforementioned market anomalies are explained by asset pricing models in the context of the JSE.

5.4 Regression Analysis

Fama and French (1992) argue that the CAPM does not explain the patterns in stock average returns related to size and value effects, and propose in 1993 a three-factor model designed to capture the aforementioned anomalies. Carhart (1997) suggests a four-factor model of asset pricing, which augments the three-factor model with a factor designed to explain the momentum effect of Jegadeesh and Titman (1993). More recently, Fama and French (2015) argue that their newly empirically derived five-factor model exhibits a stronger explanatory power than their renowned three-factor model.

This sub-section purports to examine the suitability of the asset pricing models mentioned above to capture the size, value, and momentum effects in stock average returns on the JSE over the period from 2002 to 2018. The analysis begins with the regression results of the CAPM, with a view to setting a benchmark for the multifactor asset pricing models under investigation.

5.4.1 Capital Asset Pricing Model (CAPM)

CAPM regression results of the monthly excess returns on the 18 style portfolios defined earlier, over the period from January 2002 to December 2018, are presented in Table 5.4 below.

Table 5.4 : **CAPM Regression Results**

Regression equation : $R_{Pt} - R_{ft} = \alpha_P + \beta(R_{mt} - R_{ft}) + e_{Pt}$									
Panel A: size-B/M									
	S/L	S/M	S/H	M/L	M/M	M/H	B/L	B/M	B/H
R^2	0.193	0.318	0.136	0.306	0.403	0.318	0.658	0.756	0.540
p-value	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Intercept	0.046	0.042	0.039	0.036	0.036	0.040	0.032	0.030	0.032
t-stat	12.865	15.064	10.216	14.227	15.643	14.433	16.481	17.256	12.865
p-value	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Beta (Rm-Rf)	0.548	0.595	0.480	0.533	0.589	0.600	0.841	0.961	0.848
t-stat	6.955	9.694	5.629	9.443	11.669	9.709	19.721	24.992	15.394
p-value	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Panel B: size-MOM12									
	S/Loser	S/M	S/W	M/Loser	M/M	M/W	B/Loser	B/M	B/W
R^2	0.209	0.008	0.156	0.392	0.353	0.279	0.434	0.709	0.562
p-value	0.000***	0.199	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Intercept	0.015	0.057	0.076	0.013	0.037	0.067	0.015	0.032	0.048
t-stat	4.331	4.069	23.287	4.781	15.713	26.039	4.297	19.055	18.479
p-value	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Beta (Rm-Rf)	0.575	0.401	0.437	0.698	0.540	0.499	0.941	0.829	0.926
t-stat	7.307	1.288	6.099	11.402	10.488	8.849	12.452	22.161	16.112
p-value	0.000***	0.199	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***

Note: *, **, and *** refer to 10%, 5%, and 1% level of significance respectively
S = Small ; M = Medium ; B = Big ; L = Low ; H = High ; W = Winner
For example, S/L designates the portfolios formed on small caps and low B/M

Panel A of the Table shows the results for the 9 portfolios formed on size and book-to-market (B/M), while Panel B deals with the results for the 9 size-MOM12 portfolios. The time-series regressions follow Equation 4.3 laid out in Chapter 4 (see sub-section 4.3.1.1).

5.4.1.1 Panel A Analysis (Size-B/M)

It is apparent from Panel A of Table 5.4 that the coefficient of determination, R^2, varies greatly across the 9 size-B/M portfolios. The coefficient of determination indicates the proportion of the variations in the monthly excess returns explained by the factor(s) included in the asset pricing model. The lowest R^2 value, exhibited by the portfolios formed on small caps and high B/M stocks (denoted S/H), stands at 13.6%. Meanwhile, the highest R^2 value stands at 75.6% and is related to portfolios formed on large caps and medium B/M stocks (denoted B/M). More explicitly, while only 13.6% of variations in the monthly excess returns on portfolios formed on small caps and high B/M stocks are explained by variations in the market risk premium (MRP), up to 75.6% of variations in the monthly excess returns on portfolios formed on large caps and medium B/M stocks are explained by variations in the market risk premium.

More generally, the R^2 values of the 3 portfolios formed on large caps are higher on average than those of the portfolios constructed on small and medium caps. This means that the CAPM better explains the returns on large caps portfolios than the returns on their small and medium counterparts. Nevertheless, the regression is statistically significant at 1% level for all 9 portfolios, given their p-value of 0.000.

The intercept, also known as alpha or abnormal return, is positive and statistically significant at 1% level for all 9 portfolios presented in Panel A of Table 5.4. In other words, the style portfolios outperform the market consistently over the examination period. Interestingly, the 3 large-cap-formed portfolios exhibit lower alphas than their small- and medium-cap-formed counterparts, which may infer that the style effects are stronger in small and medium caps than in large caps.

The beta coefficient, which is the slope of the regression, measures the exposure of the portfolios under investigation to market risk, and is compared to the market beta which has a value of 1.0. The beta coefficients of portfolios in Panel A are all positive and less than unity. This means that the performance of the style portfolios is positively correlated to the performance of the market; however the style returns are less volatile than the returns on the market. Besides, the relationship between the performance of style and market portfolios is statistically significant at 1% level (extremely significant).

5.4.1.2 Panel B Analysis (Size-MOM12)

Turning to Panel B of Table 5.4, it is worth noting that R^2 also varies significantly across the 9 portfolios, with the lowest one pertaining to portfolios formed on small caps and medium MOM12 portfolios (S/M), and standing at a statistically insignificant 0.8% (p-value = 0.199). This may mean that the CAPM is not a good fit for the portfolio in question. Again, the Big-Medium group exhibits the highest R^2 (70.9%), meaning that about 71% of movements in its returns are explained by movements in the market risk premium.

The 9 portfolios in Panel B consistently outperform the market over the study period, since the abnormal returns they yield are both positive and statistically significant at 1% level. Similar to Panel A, all portfolios in Panel B display positive beta coefficients which are lower than 1.0. Their returns move in tandem with the returns on the market portfolio; however, their exposure to systematic risk is lower than that of the market portfolio. Except for the Small-Medium group (S/M), the beta coefficients of the other 8 portfolios are extremely significant. The statistically insignificant beta coefficient (p-value = 0.199) of the Small-Medium group shows that the relationship between the performance of the latter and that of the market portfolio is weak, thereby supporting the earlier observation that the CAPM may not be a good fit for the portfolios formed on small caps and medium MOM12 portfolios over the study period.

The analysis of the CAPM regression results reveals that except for portfolios constructed on large caps, portfolios formed on mid caps and small caps exhibit an R^2 lower than or equal to 40%, which may be an indication that the CAPM leaves unexplained a significant proportion of variations in the average style returns under examination. These results, therefore, concur with the findings by Fama and Franch (1992) on the U.S. stock market.

5.4.2 Fama-French Three-Factor Model (FF3F)

The results of the FF3F regressions of the monthly excess returns on the 18 style portfolios built on size and book-to-market (B/M), and size and MOM12, over the period from January 2002 to December 2018, are displayed in Table 5.5 below.

Table 5.5 : FF3F Regression Results

Regression equation : $R_{Pt} - R_{ft} = \alpha_P + b_{mP}(R_{mt} - R_{ft}) + b_{sP}SMB_t + b_{vP}HML_t + e_{Pt}$

Panel A: size-B/M

	S/L	S/M	S/H	M/L	M/M	M/H	B/L	B/M	B/H
R^2	0.560	0.544	0.678	0.472	0.513	0.504	0.730	0.756	0.694
Adj. R^2	0.553	0.537	0.673	0.464	0.506	0.497	0.726	0.752	0.690
p-value	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Intercept	0.038	0.035	0.029	0.032	0.032	0.039	0.033	0.030	0.033
t-stat	13.564	14.700	11.563	13.544	14.566	15.406	18.360	16.436	15.426
p-value	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
b_mP (Rm-Rf)	0.805	0.809	0.835	0.677	0.721	0.665	0.796	0.961	0.829
t-stat	12.618	14.699	14.619	12.537	14.421	11.491	19.140	22.788	16.824
p-value	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
b_sP (SMB)	1.052	0.868	1.419	0.588	0.535	0.249	-0.175	0.000	-0.088
t-stat	10.179	9.735	15.338	6.721	6.606	2.660	-2.602	0.004	-1.109
p-value	0.000***	0.000***	0.000***	0.000***	0.000***	0.008***	0.010**	0.997	0.269
b_vP (HML)	-0.427	-0.003	0.878	-0.174	0.007	0.588	-0.354	0.016	0.555
t-stat	-5.670	-0.049	13.014	-2.729	0.111	8.613	-7.203	0.320	9.549
p-value	0.000***	0.961	0.000***	0.007	0.912	0.000***	0.000***	0.749	0.000***

Note: *, **, and *** refer to 10%, 5%, and 1% level of significance respectively

S = Small ; M = Medium ; B = Big ; L = Low ; H = High

Panel B: size-MOM12									
	S/Loser	S/M	S/W	M/Loser	M/M	M/W	B/Loser	B/M	B/W
R^2	0.559	0.015	0.408	0.488	0.417	0.396	0.554	0.710	0.575
Adj. R^2	0.552	0.001	0.399	0.481	0.408	0.387	0.548	0.705	0.569
p-value	0.000***	0.372	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Intercept	0.007	0.053	0.068	0.011	0.033	0.062	0.017	0.032	0.048
t-stat	2.473	3.622	23.812	4.041	14.410	25.300	5.307	18.009	17.859
p-value	0.014**	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
b_mP (Rm-Rf)	0.853	0.522	0.681	0.781	0.641	0.638	0.879	0.838	0.923
t-stat	13.236	1.534	10.337	12.688	11.959	11.263	11.937	20.466	14.866
p-value	0.000***	0.126	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
b_sP (SMB)	1.114	0.496	0.983	0.330	0.408	0.562	-0.264	0.038	-0.006
t-stat	10.672	0.900	9.209	3.311	4.691	6.127	-2.217	0.575	-0.063
p-value	0.000***	0.369	0.000***	0.001***	0.000***	0.000***	0.028**	0.566	0.950
b_vP (HML)	0.663	-0.251	0.197	0.418	0.086	0.013	0.556	-0.028	-0.178
t-stat	8.716	-0.625	2.530	5.745	1.363	0.190	6.394	-0.577	-2.426
p-value	0.000***	0.533	0.012**	0.000***	0.174	0.850	0.000***	0.565	0.016**
Note: *, **, and *** refer to 10%, 5%, and 1% level of significance respectively S = Small ; M = Medium ; B = Big ; W = Winner									

Panel A of the Table summarises the results for the 9 portfolios formed on size and book-to-market (B/M), while Panel B highlights the results for the 9 size-MOM12 portfolios. The time-series regressions follow Equation 4.14 described in Chapter 4 (see sub-section 4.3.1.2).

5.4.2.1 Panel A Analysis (Size-B/M)

The R^2 values reported in Panel A of Table 5.5 are much higher than those observed in Panel A of Table 5.4 (CAPM regression results), ranging between 47.2% and 75.6%. For instance, the R^2 of the small-cap-high-B/M portfolio (S/H), which is the lowest in Panel A of Table 5.4 and stands at 13.6% in the CAPM regression, jumps to 47.2% in the FF3F regression. This means that 47.2% of the fluctuations in the monthly excess returns on the S/H portfolio are accounted for by the variations in the market, small-cap, and value risk premiums. However, the R^2 value for the portfolio formed on large caps and medium B/M stocks (L/M) remains unchanged at 75.6%. Besides, the adjusted R^2 values for all 9 portfolios are very close to their respective R^2 values, suggesting that FF3F does not suffer from any overloading issue on the JSE. Lastly, the regressions are extremely significant for all 9 portfolios, as their p-values equal to 0.000.

The impressive increase in R^2 values in FF3F regressions compared to CAPM regressions provides evidence that the former asset pricing model possesses a stronger explanatory power than the latter model. Consequently, the above results align with the conclusion by prior studies that FF3F better explains average returns on the stock market than the CAPM, namely Fama and French (1993), Bahtnagar and Ramlogan (2012), and Choi (2017) on international markets, as well as Basiewicz and Auret (2010), and Sehgal, Subramaniam, and Deisting (2014) in South Africa, among others.

With regard to the intercept of the regressions, portfolios shown in Panel A of Table 5.5 all yield positive and statistically significant abnormal returns, implying that they perform better than the market in a consistent manner, even after controlling for the risks induced by the size and value effects. Besides, the portfolios exhibit positive loadings on the market risk factor, and the loadings are statistically significant at 1% level. More explicitly, the excess returns on the style portfolios vary in tandem with the returns on the market, and the market risk premium is a reliable predictor of the performance of those portfolios.

The loadings on the SMB factor, denoted b_{si}, measure the sensitivity of the excess returns on the style portfolios to variations in the small-cap risk premium. Portfolios in Panel A of Table 5.5 formed on small and medium caps load positively on SMB, and the factor loadings are extremely significant. Thus, their performance is strongly driven by small caps on the JSE over the study period. Conversely, the portfolios constructed on large caps have negative or zero factor loadings on SMB, which are statistically significant at 1% level (B/L group) or statistically insignificant (B/M and B/H groups). Thus, their performance exhibits strong to mild tilt towards the performance of large caps on the JSE.

The loadings on the HML factor, denoted b_{vi}, measure the sensitivity of the excess returns on the style portfolios to movements in the value risk premium. Portfolios in Panel A built on low B/M report negative loadings while their counterparts formed on high B/M report positive loadings on HML, and the factor loadings in both groups are statistically significant at 1% level. It can, therefore, be inferred that low B/M portfolios' performance has a strong bias towards growth stocks while the performance of their high B/M counterparts has a strong tilt towards value stocks. It can equally be inferred that SMB and HML included in FF3F capture the size effect and the value effect on the JSE respectively, identified earlier in sub-section 5.2, as the factor loadings on both factors are statistically significant at 1% level. The results align with prior studies that have documented the ability of FF3F to explain the size and value effects in the cross-section of stock returns on the stock markets, including Fama and French (1993, 2012), Arshanapalli, Coggins and Douglas (1998), Griffin (2002), and Moerman (2005) on U.S. and European markets, as well as Basiewicz and Auret (2010), Sacco (2014), Mahlophe (2015), and Tony-Okeke (2015) on the JSE, among others.

5.4.2.2 Panel B Analysis (Size-MOM12)

Panel B of Table 5.5 shows the FF3F regression results for the 9 size-MOM12 portfolios. The analysis of the R^2 values reveals a noticeable increase in the latter, compared to R^2 values in CAPM regressions reported in Panel B of Table 5.4. This supports the evidence established from Panel A that augmenting the CAPM with SMB and HML improves the explanatory power of the model and, consequently, FF3F has a stronger explanatory power than the CAPM on the JSE over the examination period. However, compared to R^2 values in Panel A of Table 5.5, the R^2 values in Panel B are much lower, which may imply that FF3F does not perform at the same level with size-MOM12 portfolios as with size-B/M portfolios, plausibly due to the momentum effect. Indeed, Fama and French (1996) establish that their three-factor model is unable to capture the momentum effect in average stock returns. Besides, except for the S/M portfolio, the adjusted R^2 values for size-MOM12 portfolios are close to their respective R^2 values, thereby confirming the non-multicollinearity problem, and the latter are statistically significant at 1% level.

In addition, the style portfolios in Panel B outperform the market consistently after accounting for the small-cap and value risks (intercepts positive and statistically significant at 1% level), and their excess returns are strongly positively correlated to the market risk premium (positive and extremely significant factor loadings on the market risk premium). The factor loadings on the small-cap risk premium are positive for portfolios formed on small and medium caps, and mostly negative for large-cap portfolios. However, the factor loading is statistically insignificant for the S/M portfolio, and for B/M and B/W portfolios as well. In other words, the performance of portfolios built on small and medium caps, whether winners or losers, are mostly strongly driven by the performance of small caps, while the performance of large caps are strongly or mildly driven by the performance of large caps on the JSE, except the B/M portfolio whose performance displays a mild bias towards small caps.

With respect to factor loadings on HML, 6 portfolios out of 9 in Panel B of Table 5.5 load positively on HML, while S/M, B/M, and B/W load negatively. More specifically, portfolios formed on loser stocks exhibit positive factor loadings with t-statistics much higher than absolute value of 2. This means that the performance of those portfolios is strongly influenced by the performance of value stocks in the market. Conversely, performance drivers of the portfolios constructed from medium and high MOM12 stocks are inconclusive, as the performance of the latter reveals strong to mild tilt towards the performance of value stocks (S/W, M/M, and M/W portfolios) and growth stocks (S/M, B/M, and B/W portfolios).

The above analysis of the FF3F regression results demonstrate that the model explains the size and value effects in average stock returns on the JSE very well and is, therefore, a suitable asset pricing model in the South African context. Moreover, FF3F performs better than the CAPM in terms of explanatory power and is therefore, a superior model to the CAPM on the JSE. However, the relatively lower performance of FF3F with portfolios formed on size and momentum (as compared to portfolios formed on size and book-to-market) suggests that the model may have failed to capture the momentum effect. Finally, looking at the t-statistics of loadings on the market, small-cap, and value risk premiums in Table 5.5, it is observed that the market risk premium exhibits the highest t-statistic on average, implying that systematic risk remains the main driver of the performance of style portfolios on the JSE over the examination period.

5.4.3 Carhart Four-Factor Model (C4F)

Table 5.6 shows the regressions results of the Carhart four-factor model (C4F) over the full study period. Similar to Table 5.4 and 5.5, Panel A of the Table presents the results for the 9 portfolios constructed from size and book-to-market ratio (B/M), and Panel B summarises the results for the remaining 9 portfolios built on size and MOM12. The time-series regressions follow Equation 4.15 described in Chapter 4 (see sub-section 4.3.1.2).

5.4.3.1 Panel A Analysis (Size-B/M)

Panel A reports high R^2 values for all 9 portfolios ranging between 46.1% (portfolio formed on small caps and low B/M) and 75.6% (portfolios formed on large caps and medium B/M). In other words, the variations in the market, small-cap, value, and momentum risk premiums account for at least 46.1% and at most 75.6% of variations in the excess returns on the 9 portfolios in the Panel. Their p-values of 0.000 demonstrate that the regression is extremely significant and, consequently, the model is a good fit in explaining returns on the JSE. Besides, their adjusted R^2 is not far from their respective R^2, signalling that there is no over-fitting problem with the regression. Notwithstanding, it is worthwhile noting that although the R^2 values are far higher than the ones produced by CAPM regressions, they are at quite the same level as the ones generated by FF3F. This probably means that the C4F has a stronger explanatory power than the CAPM on the JSE; however, it does not add much to the explanation of the excess returns on portfolios formed on size and B/M.

These results provide a hint to the independence of size, value, and momentum effects on the JSE and, therefore, support prior studies documenting the independence of those effects, such as Fraser and Page (2000).

The 9 portfolios in Panel A yield abnormal returns (intercept or alpha) which are positive and statistically significant at 1% level (t-statistics higher than absolute value of 2). This implies that despite controlling for small-cap, value, and momentum risks, the style portfolios consistently outperform the market over the study period.

Table 5.6 : C4F Regression Results

Regression equation :

$$R_{Pt} - R_{ft} = \alpha_P + b_{mP}(R_{mt} - R_{ft}) + b_{sP}SMB_t + b_{vP}HML_t + b_{wP}WML_t + e_{Pt}$$

Panel A: size-B/M

	S/L	S/M	S/H	M/L	M/M	M/H	B/L	B/M	B/H
R^2	0.461	0.530	0.565	0.463	0.487	0.501	0.724	0.756	0.695
Adj. R^2	0.450	0.520	0.557	0.452	0.476	0.491	0.719	0.752	0.688
p-value	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Intercept	0.041	0.036	0.026	0.027	0.029	0.041	0.030	0.030	0.031
t-stat	8.199	9.080	5.674	7.044	8.177	10.077	10.178	10.178	8.922
p-value	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
b_mP (Rm-Rf)	0.735	0.796	0.774	0.670	0.702	0.652	0.822	0.972	0.835
t-stat	10.391	14.246	11.661	12.279	13.669	11.228	19.547	23.064	16.938
p-value	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
b_sP (SMB)	0.689	0.729	1.017	0.460	0.390	0.192	-0.077	0.043	-0.071
t-stat	6.888	9.215	10.814	5.961	5.360	2.333	-1.300	0.727	-1.017
p-value	0.000***	0.000***	0.000***	0.000***	0.000***	0.021**	0.195	0.468	0.311
b_vP (HML)	-0.527	-0.062	0.816	-0.157	-0.003	0.546	-0.309	0.015	0.584
t-stat	-5.647	-0.839	9.314	-2.176	-0.039	7.118	-5.569	0.273	8.980
p-value	0.000***	0.402	0.000***	0.031**	0.969	0.000***	0.000***	0.785	0.000***
b_wP (WML)	-0.027	-0.011	0.081	0.107	0.056	-0.048	0.050	-0.010	0.042
t-stat	-0.326	-0.162	1.038	1.658	0.917	-0.699	1.001	-0.198	0.728
p-value	0.745	0.872	0.300	0.099*	0.360	0.485	0.318	0.843	0.468

Note: *, **, and *** refer to 10%, 5%, and 1% level of significance respectively

S = Small ; M = Medium ; B = Big ; L = Low ; H = High

Panel B: size-MOM12									
	S/Loser	S/M	S/W	M/Loser	M/M	M/W	B/Loser	B/M	B/W
R^2	0.577	0.446	0.445	0.542	0.436	0.507	0.686	0.728	0.680
Adj. R^2	0.568	0.435	0.433	0.533	0.425	0.497	0.680	0.723	0.674
p-value	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Intercept	0.029	0.017	0.049	0.030	0.030	0.041	0.048	0.025	0.024
t-stat	6.457	0.948	10.857	7.260	8.017	11.499	11.077	9.037	6.361
p-value	0.000***	0.344	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
b_mP (Rm-Rf)	0.790	1.651	0.671	0.728	0.654	0.640	0.836	0.876	0.949
t-stat	12.509	6.470	10.512	12.489	12.387	12.483	13.531	22.088	17.604
p-value	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
b_sP (SMB)	0.905	4.492	0.701	0.224	0.384	0.359	-0.176	0.131	-0.077
t-stat	10.128	12.435	7.748	2.717	5.136	4.945	-2.014	2.329	-1.003
p-value	0.000***	0.000***	0.000***	0.007***	0.000***	0.000***	0.045**	0.021**	0.317
b_vP (HML)	0.353	0.137	0.353	0.186	0.104	0.210	0.224	0.046	0.090
t-stat	4.243	0.408	4.191	2.424	1.495	3.113	2.748	0.879	1.269
p-value	0.000***	0.684	0.000***	0.016**	0.137	0.002***	0.007***	0.380	0.206
b_wP (WML)	-0.446	-0.011	0.430	-0.385	0.072	0.457	-0.660	0.123	0.515
t-stat	-5.981	-0.057	5.694	-5.588	1.151	7.545	-9.041	2.631	8.086
p-value	0.000***	0.955	0.000***	0.000***	0.251	0.000***	0.000***	0.009***	0.000***
Note: *, **, and *** refer to 10%, 5%, and 1% level of significance respectively S = Small ; M = Medium ; B = Big; W = Winner									

With respect to the market risk premium (MRP), the 9 portfolios have positive coefficients to MRP, which are extremely statistically significant, as their t-statistics are much higher than absolute value of 2 (p-value = 0.000). Thus, the variations in excess returns move in the same direction as variations in MRP. Besides, the latter is an accurate predictor of the performance of style portfolios on the JSE.

The coefficients to the SMB factor in Panel A of Table 5.6 are all positive and statistically significant for portfolios formed on small and medium caps; signalling unsurprisingly that their performance is heavily influenced by the performance of small caps on the JSE. On the contrary, the factor loadings for portfolios formed on large caps are either negative (B/L and B/H groups) or positive (B/M group), but they are all statistically insignificant. Put another way, the performance of these portfolios have a mild tilt towards the performance of large caps and small caps respectively. These results are consistent with the ones reported in FF3F regressions.

The coefficients to the HML factor reported in Panel A are negative for portfolios built on low and medium B/M (except for the portfolio built on large caps and medium B/M), and positive for portfolios constructed from high B/M. This signifies that the excess returns on low- and medium-B/M portfolios are sensitive to the performance of growth stocks while the excess returns on high-B/M are sensitive to the performance of value stocks on the JSE. Interestingly, the bias is strong for low- and high-B/M portfolios (t-statistics higher than absolute value of 2), but mild for medium-B/M portfolios. These results indicate that the C4F equally explains the value effect on the JSE over the examination period.

The coefficients to the momentum factor (WML), denoted b_{wi}, measure the sensitivity of the excess returns on the style portfolios to variations in the momentum risk premium. The coefficients reported in Panel A do not display any specific pattern, as they are positive for 4 portfolios and negative for the other 5, but not always in the same size-B/M group. For instance, portfolios formed on low B/M load negatively on WML in the small-cap group, but positively on mid- and large-cap groups. Meanwhile, portfolios formed on high B/M have positive factor loadings on small- and large-cap groups, but a negative loading on the mid-cap group. Notwithstanding, except for the M/L portfolio whose factor loading is statistically significant at 10% level, the other 8 portfolios exhibit statistically insignificant loadings on WML, implying that the momentum premium has limited influence on the performance of portfolios formed on size and B/M.

5.4.3.2 Panel B Analysis (Size-MOM12)

The C4F regression results for the 9 portfolios formed on size and MOM12 are displayed in Panel B of Table 5.6. The R^2 values reported range from 43.6% to 72.8%, which means that between 43.6% and 72.8% of movements in the performance of the 9 style portfolios are explained by the movements in the market, small-cap, value, and momentum risk premiums.

More importantly, the R^2 values are higher than the ones reported for the 9 portfolios in FF3F regressions (see Panel B of Table 5.5). The most impressive increase is reported for the S/M group whose R^2 value surged from 1.5% in FF3F results to 44.6% in C4F results. This dramatic surge probably results from the ability of the C4F to capture the momentum effect in average stock returns, left unexplained by FF3F (and CAPM). Thus, it can be inferred that adding the momentum factor to the FF3F increases its explanatory power. This result aligns with the evidence by Fama and French (2012), Czapkiewicz and Wojtowicz (2014), Sacco (2014), and Mahlophe (2015), among others, that C4F is a better predictor of stock returns than the FF3F. The adjusted R^2 and the R^2 values are close to each other for each portfolio, suggesting the absence of any multicollinearity problem in the model, while the p-values of 0.000 indicate that the C4F is a good fit for the South African stock market.

The 9 portfolios yield positive alphas and, thus, outperform the market over the study period, despite controlling for the 3 style risks under investigation (small-cap, value, and momentum). However, the alpha of the S/M portfolio is statistically insignificant (t-statistic = 0.948), which means that the portfolio outperformance is not consistent. Conversely, the remaining 8 portfolios perform better than the market in a consistent manner (t-statistic higher than absolute value of 2). Moreover, the excess returns on the portfolios move in tandem with the market, and the market risk premium (MRP) predicts the performance of the portfolios very well, given their positive and extremely significant factor loadings on the market risk factor.

Similar to the observations in Panel A, the loadings on the SMB factor in Panel B are positive for portfolios formed on small-cap and mid-cap groups, and negative for large-cap groups (except for the B/M group which is positive). In addition, the loadings are significant, except for the B/W group (t-statistic = -1.003). In other words, the performance of the latter has a mild tilt towards the performance of large caps on the market, whereas the performance of the B/Loser group is strongly driven by the performance of large caps. The returns on the small-cap and mid-cap groups are strongly influenced by the performance of small caps (t-statistic higher than absolute value of 2). Besides, the performance of 9 the portfolios has a strong to mild bias towards the performance of value stocks on the JSE, since they all load positively on the HML factor, with varying levels of statistical significance.

The coefficients to WML reported in Panel B are negative for portfolios constructed from low-MOM12 and positive for their high-MOM12 counterparts, with both groups being statistically significant at 1% level. More explicitly, the performance of portfolios formed on losers is strongly driven by the performance of loser stocks, while performance of portfolios formed on winners is strongly driven by that of winners. More importantly, this result confirms the observation made earlier that the C4F explains the momentum effect on the JSE very well, thereby concurring with the conclusions of prior studies such as Carhart (1997) and Bello (2008) on international markets, and Tony-okeke (2015) and Small and Hsieh (2017) on the South African market, among others.

The above analysis reveals that one the one hand, the C4F captures the momentum effect (along with size and value) on the JSE; on the other hand, it has a stronger explanatory power than the FF3F on the JSE over the study period. These findings support prior evidence on market anomalies and asset pricing models, both internationally and on the JSE, as mentioned above. Besides, the coefficients to the market risk factor have the highest t-statistics on average when compared to t-statistics of coefficients on the 3 other factors (SMB, HML, and WML). Thus, as with the FF3F, the performance of style portfolios under investigation is primarily driven by market risk. Nevertheless, the presence of statistically significant alphas in regression results may suggest that the C4F (and FF3F) does not account for all the patterns embedded in stock returns on the JSE.

5.4.4 Fama-French Five-Factor Model (FF5F)

Table 5.7 displays the results of the regressions of the Fama-French five-factor model (FF5F) over the full study period. Panel A of the Table shows the results for the 9 portfolios built on size and book-to-market ratio (B/M), while Panel B presents the results for the remaining 9 portfolios formed on size and MOM12. The time-series regressions follow Equation 4.16 described in Chapter 4 (see sub-section 4.3.1.2).

5.4.4.1 Panel A Analysis (Size-B/M)

Panel A of the Table reveals that the R^2 values of the 9 size-B/M portfolios are all above 50%, falling between 53.3% (M/L group) and 76% (B/L group). In other words, variations in the five risk factors (MRP, SMB, HML, RMW, and CMA) account for 53.3% of the variations in the performance of portfolios formed on mid caps and low B/M, and for 76% of the variations in the performance of portfolios formed on large caps and low B/M. Comparing these R^2 values with those from the FF3F (see Panel A of Table 5.5), it is noticed that the former are slightly higher than the latter for every portfolio. For example, the R^2 value for the M/L group rises from 47.2% in FF3F regression to 53.3% in FF5F regression, while the R^2 value for the B/L group increases from 73% in FF3F regression to 76% in FF5F regression. These results suggest that the FF5F exhibits a stronger explanatory power than the FF3F on the JSE over the study period. In this regard, the results echo the findings by Fama and French (2015) in the U.S., Cakici (2015) in the U.S. and Europe, Fama and French (2017), Zaremba and Czapkiewicz (2017) and Foye (2018) in Europe, and Mahlophe (2015) in South Africa, among others. Besides, the adjusted R^2 (close to R^2) and p-values (= 0.000) show that the regression is sound and extremely significant.

The abnormal returns (intercepts or alphas) yielded by the portfolios in Panel A are positive and statistically significant at 1% level, implying that the portfolios consistently outperform the market despite controlling for the size, value, profitability, and asset growth effects in the excess returns. Interestingly, the alphas are slightly lower than the ones reported in FF3F regressions (see Panel A of Table 5.5), providing further evidence of the superior explanatory power of the FF5F.

Table 5.7 : FF5F Regression Results

Regression equation :

$$R_{Pt} - R_{ft} = \alpha_P + b_{mP}(R_{mt} - R_{ft}) + b_{sP}SMB_t + b_{vP}HML_t + b_{rP}RMW_t + b_{cP}CMA_t + e_{Pt}$$

Panel A: size-B/M

	S/L	S/M	S/H	M/L	M/M	M/H	B/L	B/M	B/H
R^2	0.563	0.589	0.713	0.533	0.540	0.534	0.760	0.757	0.711
Adj. R^2	0.552	0.578	0.706	0.521	0.528	0.522	0.753	0.751	0.704
p-value	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Intercept	0.037	0.030	0.026	0.027	0.029	0.036	0.030	0.030	0.031
t-stat	11.883	11.765	10.109	10.872	12.523	13.224	15.778	14.917	13.156
p-value	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
b_mP (Rm-Rf)	0.786	0.817	0.825	0.689	0.716	0.670	0.820	0.953	0.839
t-stat	12.375	15.648	15.317	13.578	14.747	11.947	20.899	22.685	17.533
p-value	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
b_sP (SMB)	1.031	0.864	1.447	0.589	0.513	0.237	-0.138	-0.031	-0.096
t-stat	9.852	10.051	16.319	7.045	6.421	2.566	-2.138	-0.447	-1.213
p-value	0.000***	0.000***	0.000***	0.000***	0.000***	0.011**	0.034**	0.656	0.226
b_vP (HML)	-0.594	0.119	0.688	-0.114	-0.063	0.568	-0.333	-0.017	0.582
t-stat	-5.983	1.463	8.178	-1.435	-0.829	6.491	-5.431	-0.260	7.792
p-value	0.000***	0.145	0.000***	0.153	0.408	0.000***	0.000***	0.795	0.000***
b_rP (RMW)	0.060	0.420	0.126	0.398	0.172	0.226	0.238	-0.009	0.207
t-stat	0.524	4.443	1.293	4.328	1.957	2.226	3.344	-0.122	2.391
p-value	0.601	0.000***	0.197	0.000***	0.052*	0.027**	0.001***	0.903	0.018**
b_cP (CMA)	0.226	0.029	0.288	0.203	0.244	0.256	0.269	0.060	0.197
t-stat	2.408	0.375	3.608	2.701	3.396	3.084	4.638	0.967	2.787
p-value	0.017**	0.708	0.000***	0.008***	0.001***	0.002***	0.000***	0.335	0.006***

Note: *, **, and *** refer to 10%, 5%, and 1% level of significance respectively

S = Small ; M = Medium ; B = Big ; L = Low ; H = High

Panel B: size-MOM12									
	S/Loser	S/M	S/W	M/Loser	M/M	M/W	B/Loser	B/M	B/W
R^2	0.608	0.039	0.507	0.518	0.473	0.443	0.564	0.726	0.605
Adj. R^2	0.598	0.015	0.495	0.505	0.460	0.429	0.553	0.719	0.595
p-value	0.000***	0.159	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Intercept	0.007	0.040	0.062	0.008	0.029	0.059	0.018	0.029	0.045
t-stat	2.468	2.449	21.171	2.904	11.823	11.823	5.177	15.083	15.674
p-value	0.014**	0.015**	0.000***	0.004***	0.000***	0.000***	0.000***	0.000***	0.000***
b_mP (Rm-Rf)	0.838	0.561	0.701	0.779	0.656	0.643	0.867	0.852	0.936
t-stat	13.810	1.672	11.679	13.037	12.881	11.825	11.919	21.451	15.648
p-value	0.000***	0.096*	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
b_sP (SMB)	1.151	0.423	1.030	0.295	0.423	0.643	-0.315	0.049	0.005
t-stat	11.517	0.765	10.420	3.002	5.044	6.238	-2.626	0.755	0.048
p-value	0.000***	0.445	0.000***	0.003***	0.000***	0.000***	0.009***	0.451	0.962
b_vP (HML)	0.366	0.472	0.220	0.364	0.138	0.000	0.475	0.051	-0.211
t-stat	3.858	0.901	2.348	3.898	1.730	-0.006	4.183	0.816	-2.261
p-value	0.000***	0.368	0.020**	0.000***	0.085*	0.996	0.000***	0.415	0.025**
b_rP (RMW)	-0.086	1.167	0.472	0.213	0.337	0.285	-0.071	0.233	0.208
t-stat	-0.786	1.919	4.335	1.972	3.646	2.889	-0.538	3.238	1.920
p-value	0.433	0.056*	0.000***	0.050*	0.052*	0.004***	0.591	0.001***	0.056*
b_cP (CMA)	0.350	-0.402	0.297	0.298	0.192	0.244	0.150	0.086	0.320
t-stat	3.898	-0.809	3.343	3.372	2.543	3.025	1.390	1.458	3.619
p-value	0.000***	0.419	0.001***	0.001***	0.012**	0.003***	0.166	0.146	0.000***

Note: *, **, and *** refer to 10%, 5%, and 1% level of significance respectively

S = Small ; M = Medium ; B = Big; W = Winner

The coefficients to the market risk premium (MRP) are positive and statistically significant at 1% level (p-value = 0.000) for the 9 portfolios. In other words, the performance of the latter is positively correlated to the performance of the market, and the MRP is a reliable predictor of the performance of the portfolios under examination.

The loadings on the SMB factor displayed in Panel A are positive for the portfolios formed on small and mid caps, and negative for their large-cap counterparts. In addition, the loadings for the first 7 portfolios are extremely significant (t-statistics higher than absolute value of 2), and statistically insignificant for the last 2 portfolios (B/M and B/H groups). This reveals, with no surprise, that small caps strongly drive the performance of portfolios formed on small and mid caps, while large caps drive strongly or mildly the performance of portfolios formed on large caps.

The coefficients to the value risk factor (HML) are negative for low B/M portfolios, and positive for high-B/M portfolios, all being statistically significant at 1% level (except for the M/L group which is statistically insignificant). Thus, the returns on low-B/M portfolios are strongly or mildly influenced by the performance of growth stocks, while the returns on high-B/M portfolios exhibit a strong tilt towards the performance of value stocks on the JSE. A closer look at the t-statistics of the coefficients to HML shows that they are lower on average than the t-statistics of the loadings on HML in the FF3F regressions (see Panel A of Table 5.5). This may mean that the explanatory power of HML factor has weakened in the FF5F, thereby corroborating findings by Fama and French (2015) and Mahlophe (2015), but disagreeing with Chiah, Chai, Zhong, and Li (2016) and Jiao and Lilti (2017).

The loadings on the RMW factor, which measure the sensitivity of the returns on the style portfolios to movements in the profitability premium, are positive for 8 portfolios out of 9, with varying levels of statistical significance. Thus, it can be inferred that the performance of most style portfolios has a strong or mild bias towards the performance of stocks with robust profit on the JSE. In addition, the portfolios load positively on the CMA factor, which accounts for the sensitivity of style returns to variations in the asset growth premium. In other words, the performance of the portfolios is driven by the performance of stocks with conservative asset growth policies on the JSE over the study period. Lastly, the bias is either strong or weak, as the factor loadings exhibit diverse levels of statistical significance.

5.4.4.2 Panel B Analysis (Size-MOM12)

With regard to portfolios formed on size and MOM12, Panel B of Table 5.7 reveals that the R^2 values are mostly above 44%, except for the S/M which stands at 3.9%. This signifies that only 3.9% of the variations in the performance of the portfolio formed on small caps and medium MOM12 are explained by variations in the five risk factors. However, the R^2 values are all higher than their counterparts reported for FF3F regressions (see Panel B of Table 5.5). For instance the R^2 value for S/M stands at 3.9% in FF5F, higher than 1.5% observed in FF3F. This further supports the findings in Panel A of Table 5.7 that the FF5F tends to show a superior explanatory power to the FF3F over the study period. Nevertheless, R^2 values in Panel B of Table 5.7 tend to be lower on average than the ones reported in C4F regressions (see Panel B of Table 5.6), which may imply that the FF5F fails to capture the momentum effect. Fama and French (2016) equally document the inability of their five-factor model to capture the momentum anomaly in the U.S. Notwithstanding, R^2 and adjusted R^2 values are not far from each other (except for the S/M group), suggesting that the regression is free from any over-fitting problem. Finally, the R^2 values are statistically significant at 1% level (except for the S/M group which is statistically insignificant).

The 9 portfolios in Panel B consistently outperform the market over the study period, even after accounting for the style effects under consideration (size, value, momentum, profitability and asset growth), given that the factor loadings are positive and statistically significant (t-statistics higher than absolute value of 2). Again, as observed in Panel A, the alphas are less stronger compared to their counterparts in FF3F regressions (see Panel B of Table 5.5), as the former's t-statistics are slightly lower than the latter's.

The portfolios exhibit positive and statistically significant loadings on the market risk factor, demonstrating that the performance of the portfolios move in tandem with the market, and the MRP predicts their performance very well. Except for the B/Loser group, the performance of the other 8 portfolios has a strong to mild tilt towards the performance of small caps in the market. However, the SMB factor loadings for the B/M and B/W groups are statistically insignificant. Lastly, the performance of the B/Loser portfolio is strongly driven by the performance of large caps on the JSE. Except for the B/W group, coefficients to the HML factors for portfolios in Panel B are positive, but with differing levels of statistical significance, meaning that their performance has a strong or mild bias towards the performance of value stocks on the market. Conversely, the returns on the B/W portfolio are strongly driven by the performance of growth stocks in the market (t-statistic higher than absolute value of 2). Besides, the t-statistics of HML factor loadings are on average lower than their counterparts in FF3F (see Panel B of Table 5.5), thus supporting the likely weakening explanatory power of the HML factor in the FF5F.

The coefficients to the RMW factor are mostly positive and statistically significant, but negative and statistically insignificant for the S/Loser and B/Loser groups. Thus, while the performance of the latter exhibits a mild tilt toward the performance of weak-profit stocks, the performance of the 7 other portfolios has a strong bias towards the performance of stocks with robust profits. Similarly, the loadings on the CMA factor in panel B are mostly positive (except for the S/M group), but with varying degrees of significance. Thus, the behaviour of the S/M portfolio can be assimilated to the behaviour of companies that invest heavily while the remaining portfolios behave like companies that invest with caution.

The analysis above reveals that augmenting the FF3F with RMW and CMA improves its explanatory power, making the FF5F a stronger model than the FF5F on the JSE. Moreover, the HML factor seems to lose some of its explanatory power in the FF5F. Furthermore, the FF5F seems to be a suitable asset pricing model in explaining stock returns on the JSE, although it likely fails to explain the momentum effect. Finally, and as earlier observed in the analysis of C4F regression results, the FF5F regressions exhibit positive and statistically significant alphas, probably signalling that the model does not capture all the patterns influencing stock returns on the JSE.

5.5 Conclusion

The analysis of the average monthly excess returns on portfolios formed on size and B/M (9 portfolios) and size and MOM12 (9 portfolios) over the period from January 2002 to December 2018 uncovers the existence of the size, value, and momentum effects on the JSE over the full study period. In addition, a similar analysis on sub-periods corresponding to the upward and downward phases of the business cycle identified throughout the study period reveals that the magnitude of these style effects tends to fluctuate depending on the economic climate. More specifically, the size effect tends to weaken, disappear or reverse during downward periods, whereas the value effect tends to strengthen during these periods. The momentum effect equally tends to weaken during downward periods, but remains stronger than the size effect. These results concur with prior international and South African evidence with regard to the existence of size, value, and momentum effects on stock markets, as identified earlier. More importantly, the above findings hint at the cyclical behaviour of the style effects under investigation.

The examination of the regression results of CAPM and associated multifactor asset pricing models shows that the CAPM is unable to capture the size, value, and momentum effects on the JSE, and equally leaves unexplained significant trends in average stock returns. Meanwhile, the FF3F captures size and value, but not the momentum effect. However, it is a better predictor of returns than the CAPM on the JSE. The C4F proves superior to FF3F as it explains the momentum effect in addition to size and value. Finally, the FF5F exhibits a stronger explanatory power than the FF3F, though it fails to account for the momentum effect. Besides, while the explanatory power of the HML factor tends to diminish in the FF5F, market risk shows up as the primary driver of stock returns on the JSE. At last, the multifactor asset pricing models seem not to capture all patterns embedded in stock returns, as the regression alphas are positive and statistically significant for most portfolios in the three multifactor models under investigation. These findings equally support previous studies and imply that a more efficient asset pricing model might be needed to explain stock returns on the market more accurately.

CHAPTER 6 – CYCLICALITY OF SIZE, VALUE, AND MOMENTUM EFFECTS ON THE JSE

6.1 Introduction

The analysis and discussion carried out in Chapter 5 have revealed that the size, value, and momentum anomalies are present on the Johannesburg Stock Exchange (JSE) over the period from 1 January 2002 to 31 December 2018. Furthermore, the analysis of the excess monthly returns on portfolios formed on size and book-to-market ratio (B/M), and size and prior-12-month returns (MOM12) over sub-periods corresponding to the phases of the South African business cycle embedded in the examination period, has established that the magnitude of the style effects is not constant over time, as the effects tend to be stronger in some periods than in others. These results, therefore, suggest that the size, value, and momentum effects might be cyclical on the JSE.

This chapter investigates whether the size, value, and momentum effects exhibit a cyclical behaviour on the JSE over the period January 2002 – December 2018. The analysis focuses on returns on the following style portfolios: SMB (small minus big) for the size effect, HML (high minus low) for the value effect, and WML (winner minus loser) for the momentum effect. More specifically, the mean, standard deviation, and Sharpe ratio of the small-cap risk premium, value risk premium, and momentum risk premium are analysed over the whole period (2002 - 2018), and over the sub-periods identified in Chapter 4 (sub-section 4.2.1): two upward periods (2002 – 2007 and 2009 - 2013) and two downward periods (2007 – 2009, and 2013 - 2018). The analysis is designed to determine whether the aforementioned style premiums are constant (pervasive) over the different phases of the South African economic cycle, or, instead, whether they vary with regard to prevailing economic conditions. Besides, the analysis uncovers whether the movements in style premiums are positively correlated to the state of the economy (procyclical) or, rather, negatively correlated to the state of the economy (countercyclical).

The chapter begins with a succinct summary of the prior empirical evidence on the cyclicality of size, value, and momentum effects on capital markets, and of the objectives of the chapter as well (Section 6.2). Then, the chapter presents and discusses the findings pertaining to the behaviour of the small-cap, value, and momentum premiums on the JSE over the examination periods and sub-periods earlier identified (Section 6.3). Finally, the chapter closes with a discussion on the cyclical nature of the style effects under investigation (Section 6.4).

6.2 Chapter Objectives

The literature review presented in Chapter 3 (Section 3.4) has showed that a large number of studies on international markets document a cyclical behaviour of size, value, and momentum premiums. More specifically, size and momentum premiums tend to increase in expansionary and bull periods, and decrease during bear and recessionary periods, while the value premium instead strengthens during economic recessions and decrease during economic expansions (see for example Krueger and Johnson, 1991; Liew and Vassalou, 2000; and Sarwar, Mateus, and Todorovic, 2017 for the size premium; Krueger and Johnson, 1991; Kwag and Lee, 2006; and Gulen, Xing, and Zhang, 2011 for the value premium; Chordia and Shivakumar, 2002; Kim, Roh, Min, and Byun, 2014; and Daniel and Moskowitz, 2016 for the momentum premium). However, the cyclical behaviour of these style effects has been given little attention on the JSE, with the few studies available on the subject matter providing mixed conclusions (see for instance Graham and Uliana 2001; Hsieh, 2015; and Barnard and Bunting, 2015).

Thus, the two main goals of this chapter are as follows:

- To determine whether size, value, and momentum premiums vary with the business cycle (cyclical behaviour) on the JSE over the period from 1 January 2002 to 31 December 2018;
- To establish the nature of the relationship of the style premiums with the business cycle (procyclical or countercyclical) over the examination period.

6.3 Performance Evaluation of Style Factors

Performance evaluation of the risk factors under investigation (size, value, and momentum) is carried out over the full study period and over the sub-periods identified above. The tools used for the analysis include the mean, standard deviation, and Sharpe ratio.

6.3.1 Full Period (2002 - 2018)

The performance evaluation measures of the small-cap, value, and momentum factor portfolios for the period from January 2002 to December 2018 are presented in Table 6.1, and figures 6.1 and 6.2 below. The performance measures of the market risk factor are equally included for comparative purposes.

Table 6.1 : Descriptive Statistics of Average Monthly Returns on Risk Factors for the Period 2002-2018

	Rm-Rf	SMB	HML	WML
Mean	0.0052	0.0077	-0.0003	0.0475
Standard Deviation	0.0451	0.0322	0.0357	0.0402
Sharpe Ratio	-0.0229	0.0460	-0.1834	1.0259

According to Table 6.1, the small-cap risk factor (SMB) and momentum risk factor (WML) yield positive premiums over the examination period, averaging 0.77% and 4.75% per month respectively. Conversely, the value risk factor (HML) exhibits a negative premium of 0.03% per month on average over the period 2002 – 2018. This means that on average, small caps and past winners outperform large caps and past losers respectively, whereas value stocks underperform growth stocks over the full study period. Besides, the average monthly small-cap and momentum premiums are higher than the market risk premium (Rm - Rf, or MRP), which stands at 0.52%. Furthermore, the return on the WML portfolio is much higher than the returns on the other portfolios, which is clearly represented in Figure 6.1. This signifies that the momentum style delivers the highest average return among the styles under investigation over the period of study.

Looking at the risk inherent to the style premiums (proxied by standard deviation), Table 6.1 reveals that the WML portfolio exhibits a higher standard deviation than the SMB portfolio (4.02% against 3.22%). In other words, the higher return on the momentum factor comes with higher risk. This result is consistent with the finance theory which stipulates that the higher the risk, the higher the returns. The risk on the HML portfolio stands between the other 2 style portfolios, at 3.57%. Interestingly, the standard deviation of the market risk premium stands at 4.51%, which is higher than the standard deviation of the small-cap and momentum premiums. This means that although the small-cap and momentum premiums are higher than the MRP, they are perceived as less risky than the market. Figure 6.1 shows that the market risk premium has the highest volatility compared to the style premiums under investigation.

Figure 6.1: Mean and Standard Deviation of Factor Premiums over the Period 2002 - 2018

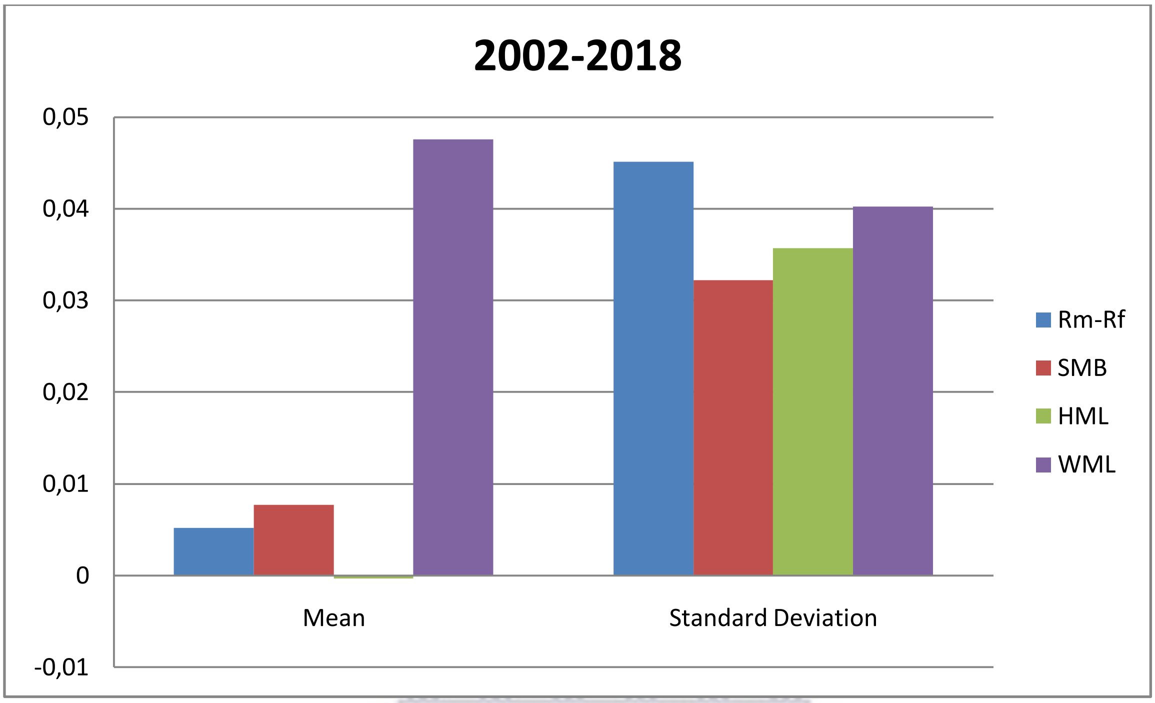
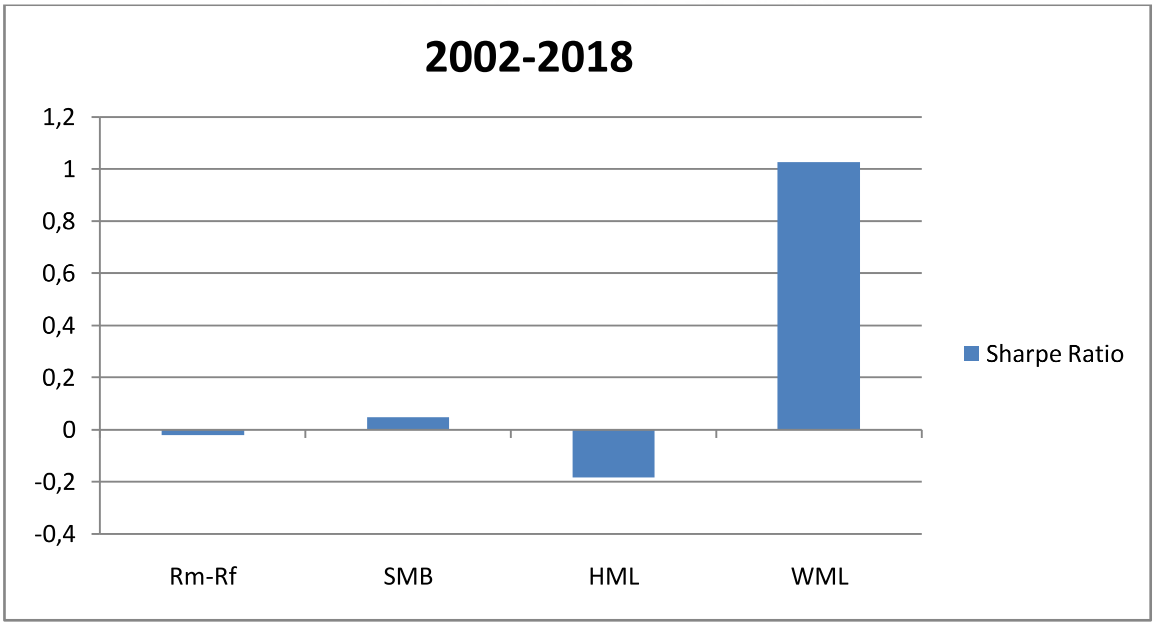


Figure 6.2: Sharpe Ratio of Factor Premiums over the Period 2002 -2018



The higher return on the WML factor portfolio coupled with its relatively low standard deviation logically delivers an impressive Sharpe ratio of 1.03, which is the highest Shape ratio reported in Table 6.1 and depicted in Figure 6.2. The next highest Sharpe ratio is delivered by the small-cap risk premium, and stands at 0.05, owing to the high premium coupled with a lower standard deviation compared to the HML portfolio and the market. The latter rather exhibit negative Sharpe ratios as they underperform the risk-free asset. More specifically, the MRP's and HML's Sharpe ratios are -0.02 and -0.18 respectively.

The analysis above demonstrates that from a risk-adjusted perspective, the momentum and small-cap factor portfolios deliver superior returns compared to the value factor portfolio and the market over the full study period and are, therefore, on average the most profitable investment styles out of the 3 styles under investigation. Notwithstanding, the sub-period analysis will shed light on whether the above performance holds throughout the study period.

6.3.2 Upward Periods (2002 - 2007 and 2009 - 2013)

After analysing the small-cap, value, and momentum premiums on the JSE over the whole study period, a further analysis is carried on the two upward phases of the business cycle identified in the examination period: the pre-2008 financial crisis period (January 2002 - November 2007) and the post-2008 crisis period (September 2009 – November 2013).

6.3.2.1 Upward Period 2002 – 2007

The average monthly mean, standard deviation, and Sharpe ratio of the small-cap, value, and momentum premiums for the period from January 2002 to November 2007 are reported in Table 6.2, and figures 6.3 and 6.4 below.

Table 6.2 reports a positive average monthly premium for all 3 style risk factors (SMB, HML, and WML). More specifically, the momentum premium is the highest and is equal to 5.24%, followed by the small-cap premium, which is equal to 1.88%. The value premium is the lowest and stands at 0.25%. The positive style premiums signify that small caps, value stocks, and past winners perform better than large caps, growth stocks, and past winners respectively, over the period 2002 – 2007 on the JSE. Lastly, SMB and WML portfolios yield higher premiums than the market, while the HML portfolio's is lower than the latter's, as depicted in Figure 6.3.

Table 6.2: Descriptive Statistics of Average Monthly Returns on Risk Factors for the Period 2002-2007

	Rm-Rf	SMB	HML	WML
Mean	0.0114	0.0188	0.0025	0.0524
Standard Deviation	0.0474	0.0419	0.0310	0.0412
Sharpe Ratio	0.0863	0.2736	-0.1544	1.0953

The outperformance of small caps over large caps on the JSE over the 2002 – 2007 upward phase of the business cycle is consistent with empirical studies pertaining to the cyclicality of the style effect. For example, Krueger and Johnson (1991) and Bhardwaj and Brooks (1993) show that small caps perform better than large caps during periods of economic expansion in the U.S. Other studies documenting a positive small-cap premium during bull and expansionary periods include Kim and Burnie (2001), Rutledge, Zhang, and Karim (2007), and Sarwar et al. (2017), among others. Similarly, the positive value premium result supports earlier findings that value stocks yield higher returns than growth stocks during periods of expansion, such as Kwag and Lee (2006), Athanassakos (2009), and Hsieh (2015). Finally, the outperformance of winners over losers in the upward period concurs with the findings by Chordia and Shivakumar (2002) and Cooper, Gutierrez, and Hameed (2004), who show that momentum strategies yield significant profits in expansionary economic periods on the U.S. stock market.

It should equally be noted that the style premiums reported in Table 6.2 are higher than the ones reported in Table 6.1 for the full study period (2002 - 2018). For instance, the small-cap premium amounts to 0.77% in Table 6.1 against 1.88% in Table 6.2, while the momentum premium stands at 4.75% in Table 6.1 versus 5.24% in Table 6.2. More important, the value premium moves from negative to positive territory (-0.03% in Table 6.1 versus 0.25% in Table 6.2). This confirms the results previously established in sub-section 5.3.2.1 that the style effects are stronger in the 2002 - 2007 upward period as compared to the full period.

Figure 6.3: Mean and Standard Deviation of Factor Premiums over the Period 2002 - 2007

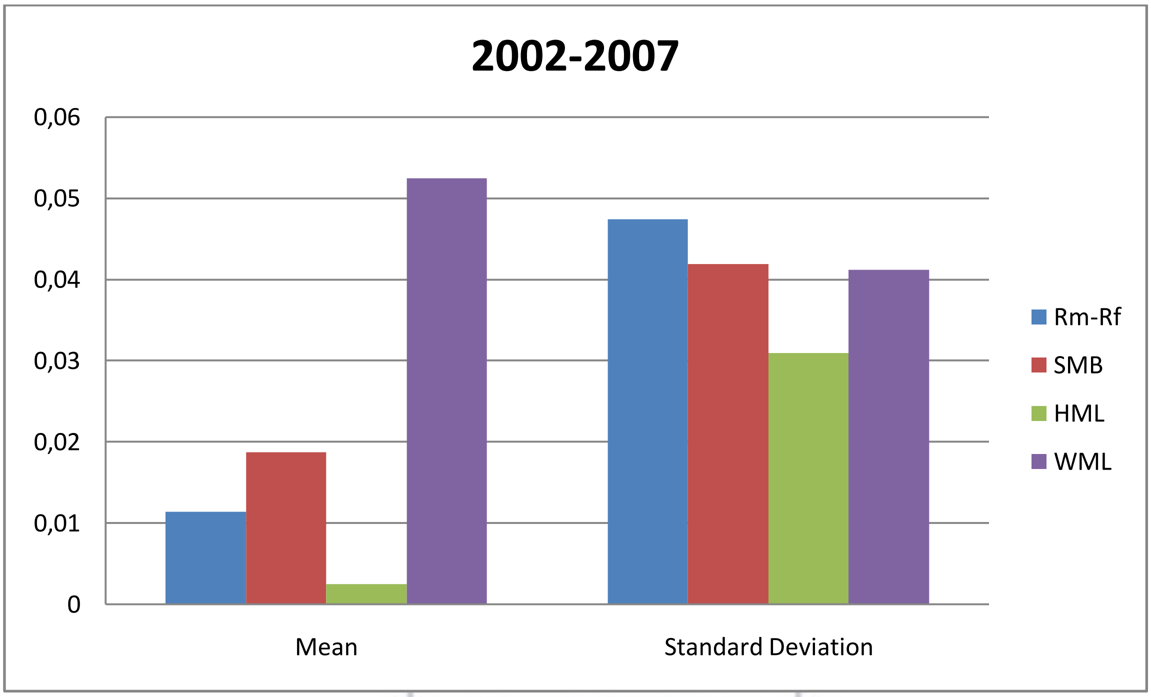
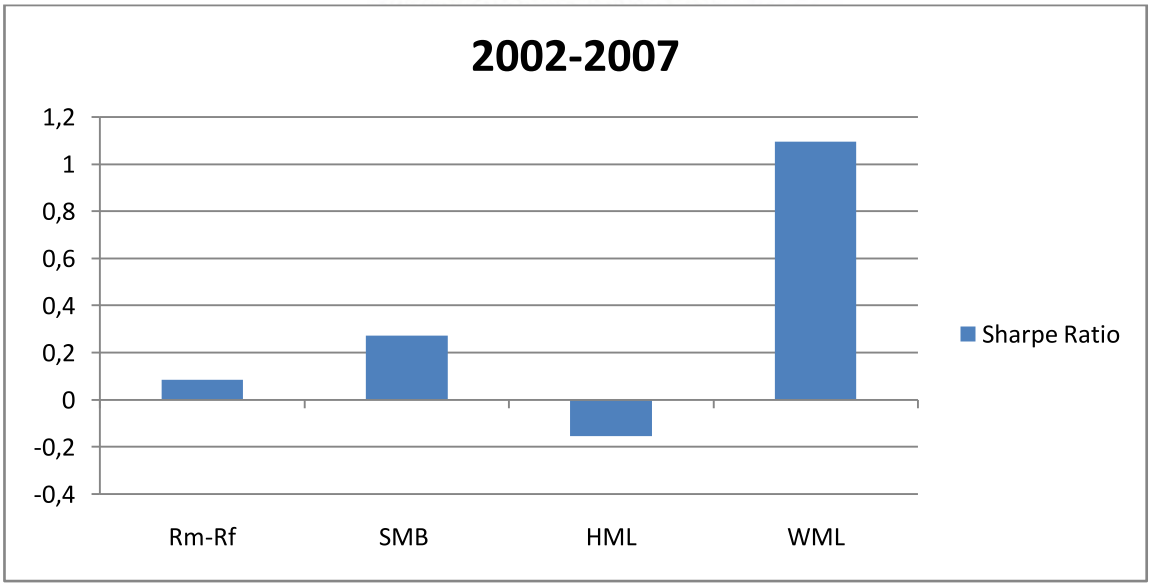


Figure 6.4: Sharpe Ratio of Factor Premiums over the Period 2002 -2007



The standard deviations reported in Table 6.2 reveal that the small-cap premium is riskier than the momentum premium, though the gap is not large (4.19% and 4.12% respectively). The former is equally riskier than the value premium (4.19% and 3.10% respectively). Contrary to observations in Table 6.1, the small-cap premium displayed in Table 6.2 comes with higher risk than the momentum premium, even though the WML factor portfolio yields a higher return than the SMB factor portfolio. This suggests that over the period 2002 – 2007, the small-cap premium is more volatile than the momentum premium (and the value premium as well). However, and similar to the observation in the full study period above, the market risk premium, with a standard deviation of 4.74%, is the most volatile of all the factor premiums reported in Table 6.2, and depicted in Figure 6.3. Lastly, the risks inherent to the factor premiums are higher on average over the 2002 - 2007 upward period than over the full examination period (see Table 6.1), except for the value premium, whose standard deviation is equal to 3.57% in Table 6.1, but falls to 3.1% in Table 6.2. The higher standard deviations may not be surprising considering that the 2002 - 2007 is a period of economic prosperity whereas the 2002 – 2018 period covers both expansionary and recessionary periods and, therefore, smoothens the volatility of the factor premiums.

With regard to risk-adjusted performance, the WML portfolio yields a Sharpe ratio of 1.0953 as reported in Table 6.2 and depicted in Figure 6.4, which is the highest ratio among the 3 factor portfolios. This strong Sharpe ratio is favoured by high returns and relatively low standard deviation. The SMB comes next with a Sharpe ratio of 0.2736 while the market delivers a ratio of 0.0863. The poorest risk-adjusted performance is exhibited by the HML portfolio with a negative Sharpe ratio of -0.1544. In other words, the WML portfolio delivers the best risk-adjusted performance on the JSE over the expansionary period 2002 – 2007, while the worst risk-adjusted performance pertains to the HML portfolio. Nevertheless, the Sharpe ratios of all 3 style portfolios are higher than the ones reported for the full period (Table 6.1), which means the performance of the portfolios was above average during the pre-2008 financial crisis period.

As observed in Chapter 5 (sub-section 5.3.2.1), the higher premiums observed over the period 2002 – 2007 were driven by the economic expansion experienced by the South African economy subsequent to the dot.com crash and the restructuring of the JSE.

6.3.2.2 Upward Period 2009 – 2013

Table 6.3 displays the descriptive statistics (mean, standard deviation, and Sharpe ratio) of the small-cap, value, and momentum premiums for the period spanning December 2009 - November 2013. The graphical representation is presented in Figures 6.5 and 6.6 below.

Table 6.3: Descriptive Statistics of Average Monthly Returns on Risk Factors for the Period 2009-2013

	Rm-Rf	SMB	HML	WML
Mean	0.0100	0.0066	-0.0203	0.0490
Standard Deviation	0.0374	0.0211	0.0238	0.0277
Sharpe Ratio	0.1401	0.0861	-1.0509	1.5952

It is apparent from Table 6.3 and Figure 6.5 that the WML portfolio yields the highest average monthly premium over the period 2009 – 2013, which amounts to 4.9%. Interestingly, the small-cap premium, which is equal to 0.66% per month, is lower than the market risk premium of 1% per month. The lowest premium is exhibited by the HML factor portfolio, standing at -2.03% per month over the sub-period. This signifies that the market portfolio outperforms the size and value factor portfolios over this second upward period.

These results suggest that winner stocks and small caps outperform loser stocks and large caps respectively over the period 2009 – 2013, whereas value stocks underperform growth stocks. This echoes the findings reported in Chapter 5 (sub-section 5.3.2.2) where a reversal of the value effect is observed over the sub-period under consideration. More importantly, the negative value premium is inconsistent with the evidence by Kwag and Lee (2006), Athanassakos (2009), and Hsieh (2015) that value stocks outperform growth stocks during economic expansions. These contradictory results may be explained by the fact that the period 2009 – 2013 was a period during which the South African economy was just rebounding from the 2008 global financial crisis and was, consequently, more of a recovery period in which the economy was not yet operating at an optimum level.

Figure 6.5: Mean and Standard Deviation of Factor Premiums over the Period 2009 - 2013

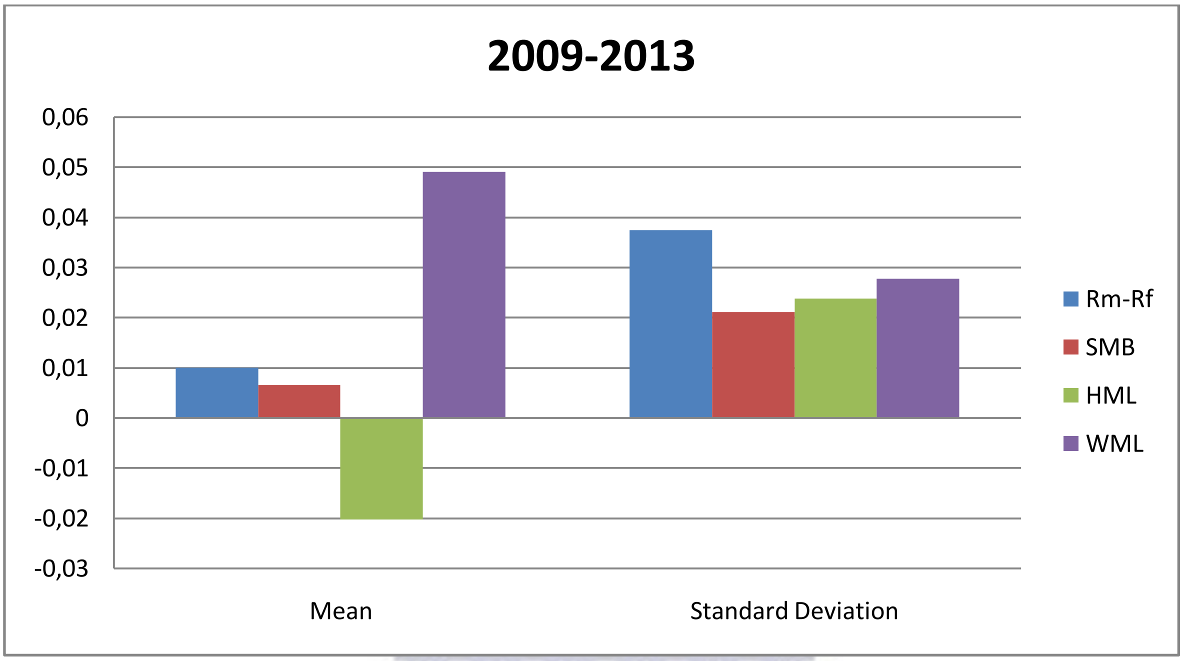
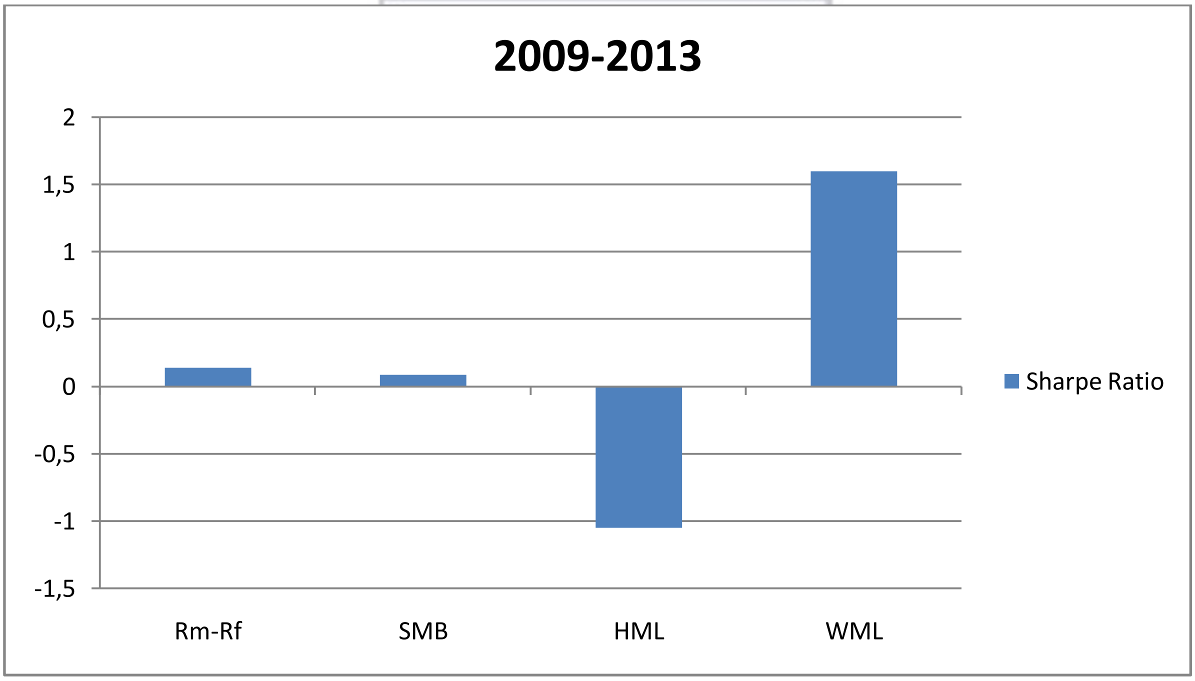


Figure 6.6: Sharpe Ratio of Factor Premiums over the Period 2009-2013



In this regard, it can be inferred that during periods of South African economic recovery, growth stocks tend to outperform value stocks, leading to a negative value premium on the JSE.

The analysis of the average monthly premium in Table 6.3 finally reveals that the SMB and HML portfolios are less profitable than the market portfolio on the JSE over the period from 2009 to 2013, while the WML portfolio remains the top performer over the period. Nevertheless, the premium levels are lower on average than the levels observed during the period 2002 – 2007. For example, the monthly average momentum premium stands at 4.9% in the 2009 - 2013 period compared to 5.24% in the 2002 – 2007 period (see Table 6.2). This lower performance of the factor portfolios is probably due to the recovery state of the South African economy at the time.

With respect to the risk embedded in the premiums, Table 6.3 and Figure 6.5 reveal that among the three style premiums, the momentum premium exhibits the highest standard deviation (2.77%) compared to value and small-cap premiums (2.38% and 2.11% respectively). This means that over the period 2009 – 2013, the momentum premium is more volatile than the small-cap and value premiums. However, the market risk premium's standard deviation is higher than the momentum premium's, as the former is equal to 3.74%. In other words, the market portfolio is riskier than the WML portfolio (as well as the SMB and HML portfolios) over the period, even though it yields a lower average premium than the latter.

Unsurprisingly, the combination of the WML portfolio's highest premium and relatively low standard deviation yields the highest Sharpe ratio reported in Table 6.3 and depicted in Figure 6.6. Indeed, the Sharpe ratio of the momentum premium amounts to 1.595, while the small-cap premium's and the value premium's Sharpe ratio are equal to 0.086 and -1.051 respectively. This signifies that the WML portfolio still performs better than the other 2 factor portfolios when the premiums are adjusted for risk, making it the most profitable portfolio over the period 2009 – 2013. The market risk premium delivers the second highest Sharpe ratio next to the momentum premium, and the ratio stands at 0.14. In other words, the market portfolio still outperforms the SMB and HML portfolios over the period when risk is controlled for.

The analysis of the style premiums on the JSE over the upward phases of the economic cycle shows that results are globally in line with previous studies which contend that the small-cap, value, and momentum premiums are positive during periods of economic expansion and bull markets, as small caps, value stocks, and past winner stocks tend to outperform their large-cap, growth, and past loser counterparts. However, the negative value premium reported for the 2009 – 2013 period contradicts findings from prior studies, and may hint on the fact that value stocks underperform growth stocks in recovery times on the JSE.

6.3.3 Downward Periods (2007 - 2009 and 2013 - 2018)

Having discussed the performance of the SMB, HML, and WML factor portfolios over the upward phases of the South African business cycle identified in the examination period, this study then focuses on their performance in downward phases: the crisis period (December 2007 - August 2009), and the post-recovery period (December 2013 – December 2018).

6.3.3.1 Downward Period 2007 – 2009

The performance evaluation measures of the SMB, HML, and WML portfolios over the period 2007 – 2009 are displayed in Table 6.4 and depicted in Figures 6.7 and 6.8 below. The market risk premium is equally included for comparative purposes.

Table 6.4 reveals positive premiums for HML and WML portfolios, and a negative premium for the SMB portfolio. More specifically, the WML portfolio yields the highest average monthly premium over the period 2007 – 2009, amounting to 3.9%. The HML portfolio generates the second highest premium of 1.65% per month on average. Conversely, the SMB portfolio's premium falls in a negative territory, standing at -1.15% per month on average. Besides, the market risk premium is negative and is equal to -1.22% per month on average over the period under consideration. These results imply that during the period from December 2007 to August 2009, winner stocks and value stocks outperform loser stocks and growth stocks respectively, whereas small caps underperform large caps on average on the JSE. In addition, the market underperforms risk-free securities.

Table 6.4: Descriptive Statistics of Average Monthly Returns on Risk Factors for the Period 2007-2009

	Rm-Rf	SMB	HML	WML
Mean	-0.0122	-0.0115	0.0165	0.0390
Standard Deviation	0.0754	0.0285	0.0307	0.0475
Sharpe Ratio	-0.2704	-0.6911	0.2704	0.6491

A comparative analysis of average monthly style premiums between the 2007 – 2009 downward period and the aforementioned upward periods uncovers interesting results. The value premium reported in this downward period (1.65%, see Table 6.4) is higher than the one reported in the period 2002 – 2007 (0.25%, see Table 6.2) and definitely higher than the one displayed in the period 2009 – 2013 (-2.03%, see Table 6.3). This suggests that the outperformance of value stocks over growth stocks is much stronger during downward economic periods than during upward periods on the JSE. These findings support the stronger value effect reported in Chapter 5 (sub-section 5.3.2.1) for the period 2007 – 2009. More interesting, the results concur with prior international and South African evidence that the value premium tends to be larger during recessionary periods than during expansionary periods.

Indeed, Krueger and Johnson (1991) contend that low price-to-earnings (P/E) portfolios (value portfolios) outperform high price-to-earnings portfolios (growth portfolios) on the U.S. stock market during economic recessions and bear markets periods. Xing and Zhang (2005) report a larger value premium in the U.S. during turbulent economic times, and this evidence is echoed by subsequent studies such as Kwag and Lee (2006), Athanassakos (2009), Gulen, Xing, and Zhang (2011), and Barnard and Bunting (2015). More specifically, Kwag and Lee (2006) find that value stocks perform better than growth stocks in both expansionary and contractionary periods; however, the outperformance is stronger in the latter periods.

Figure 6.7: Mean and Standard Deviation of Factor Premiums over the Period 2007 - 2009

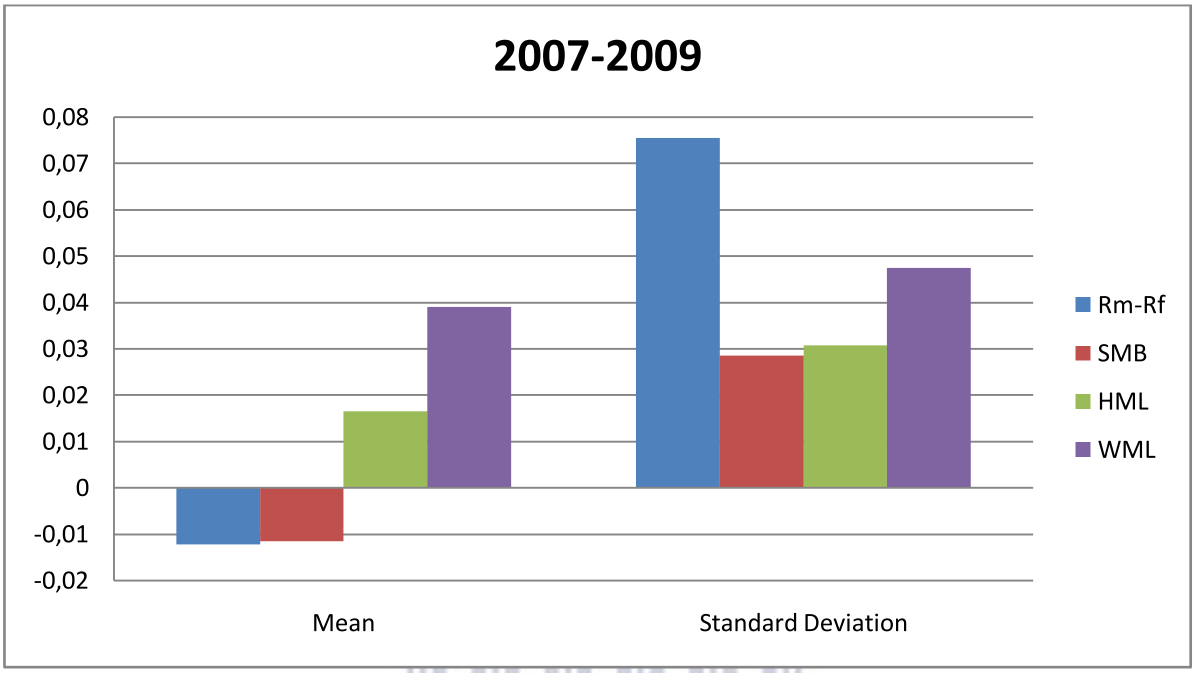
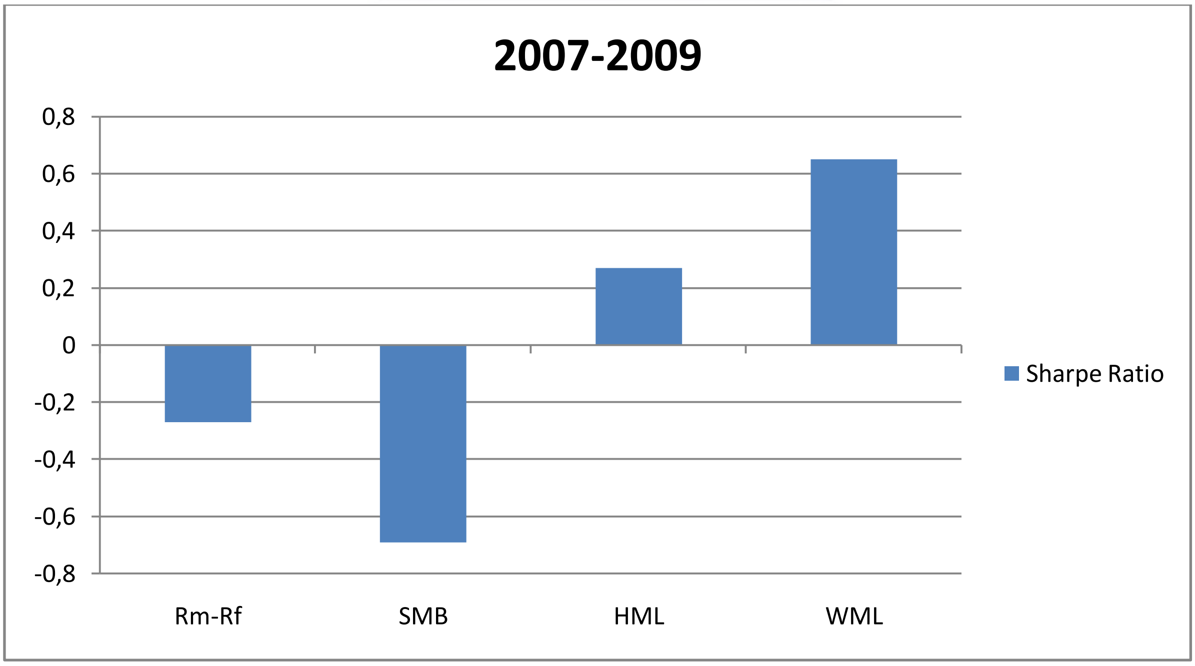


Figure 6.8: Sharpe Ratio of Factor Premiums over the Period 2007-2009



With regard to the SMB portfolio, the negative average monthly small-cap premium presented in Table 6.4 (-1.15%) confirms the reversal of the size effect observed in Chapter 5 (sub-section 5.3.2.1) over the period under consideration, and aligns with evidence from prior studies on international markets that small caps underperform large caps during periods of poor economic conditions (see for instance Krueger and Johnson, 1991; Bhardwaj and Brooks, 1993; Kim and Burnie, 2001; and Switzer and Pickard, 2016; among others). The results equally support conclusions by prior studies on the South African stock market. For example, Barnard and Bunting (2015) find that large stocks perform better than small stocks on the JSE during the financial crisis period.

The average monthly momentum premium reported for the 2007 – 2009 period in Table 6.4 (3.9%) is lower than the one recorded during upward periods (5.24% for the period 2002 – 2007, see Table 6.2; and 4.9% for the period 2009 – 2013, see Table 6.3). This means that although winners keep outperforming losers during the period, the outperformance is not as strong as during upward periods. These results are consistent with the findings by Cooper et al. (2004) as they show that momentum profits during downward market periods are not as large as during upward market periods in the U.S. over the 1929 – 1995 period. However, the results disagree with Sarwar et al. (2017) who find on the U.K. stock market that there is no noticeable difference between momentum profits in times of economic expansion and momentum profits in times of economic recession, in their study covering the period from 1982 to 2014. These differing results are probably due to differences in datasets used in the aforementioned studies.

Table 6.4 and Figure 6.7 reveal that the WML premium is the most volatile premium among the three style premiums over the period 2007 – 2009, as its standard deviation stands at 4.75%, against 3.07% for the value premium and 2.85% for the small-cap premium. Nevertheless, the market risk premium tops them all in terms of risk with a standard deviation of 7.54%.

In terms of risk-adjusted performance, the WML portfolio performs best. Indeed, its Sharpe ratio, as reported in Table 6.4 and shown in Figure 6.8, is equal to 0.649. This is due to the high momentum premium coupled with a relatively low standard deviation. The next best performer is the HML factor portfolio which delivers this time a positive Sharpe ratio of 0.27, resulting from a value premium higher than the returns on government bills. The Sharpe ratio for the SMB portfolio slips into negative territory and amounts to -0.691, caused by the negative premium generated over the period. The market risk premium equally exhibits a negative Sharpe ratio (-0.27), but the SMB portfolio remains the worst performer over the period 2007 – 2009, when risk is controlled for. These findings suggest that during the 2008 financial crisis period, value and momentum investment styles are the most profitable style-based investment strategies on the JSE, among the styles under investigation.

6.3.3.2 Downward Period 2013 – 2018

The descriptive statistics of the style premiums under consideration (SMB, HML, and WML) for the period 2013 – 2018 are displayed in Table 6.5 and Figures 6.9 and 6.10 below, along with those of the market risk premium.

The Table reveals that the WML portfolio yields the largest average monthly premium over the period, which is equal to 4.35%. The HML portfolio is next in the ranking with a premium of 0.73% per month on average, while the SMB portfolio comes last with 0.24% average monthly premium. Thus, during the period 2013 – 2018, small caps, value stocks, and winner stocks yield higher returns than large caps, growth stocks, and loser stocks respectively. The market portfolio yields a premium indistinguishable from zero.

A comparative analysis shows that the small-cap and momentum premiums are larger in the second downward period than in the first one. Indeed, the small-cap premium surges from -1.15% in the period 2007 – 2009 (see Table 6.4) to 0.24% per month in the period 2013 – 2018 (Table 6.5). Similarly, the momentum premium rises from 3.9% in the first period to 4.35% in the second period. However, the performance level is still below the levels observed during upward periods. For example, the average monthly small-cap premium stands at 1.88% and 0.66% over the periods 2002 – 2007 and 2009 – 2013 respectively, while the momentum premium amounts to 5.24% and 4.9% per month on average over the periods 2002 – 2007 and 2009 – 2013 respectively.

Table 6.5: Descriptive Statistics of Average Monthly Returns on Risk Factors for the Period 2013-2018

	Rm-Rf	SMB	HML	WML
Mean	0.0000	0.0024	0.0073	0.0435
Standard Deviation	0.0315	0.0226	0.0437	0.0451
Sharpe Ratio	-0.1767	-0.1382	0.0390	0.8413

This means that on the one hand, the SMB and WML factor portfolios perform better during the second downward period than during the first one, probably due to the fact that the economic decline is not as severe in 2013 – 2018 as in 2007 – 2009, which is more of a financial crisis period. On the other hand, during the 2013 – 2018 period, the portfolios perform below their respective levels in upward periods. These results confirm the observations made in Chapter 5 (sub-section 5.3.3.2) that the size and momentum effects are stronger during the second downward period compared to the first one, but are weaker than in the two upward periods.

With regard to the momentum premium, the above findings further support prior evidence asserting that although the premium is positive in downward phases of the economic cycle, it is not as large as in upward phases (see for instance Cooper et al., 2004). The behaviour of the small-cap premium provides less clear-cut results, as the premium is still positive in the second downward period, although it reduces significantly. This is inconsistent with conclusions by earlier studies that small caps underperform large caps during recessionary periods (Krueger and Johnson, 1991; Bhardwaj and Brooks, 1993; and Barnard and Bunting, 2015; among others).

Figure 6.9: Mean and Standard Deviation of Factor Premiums over the Period 2013-2018

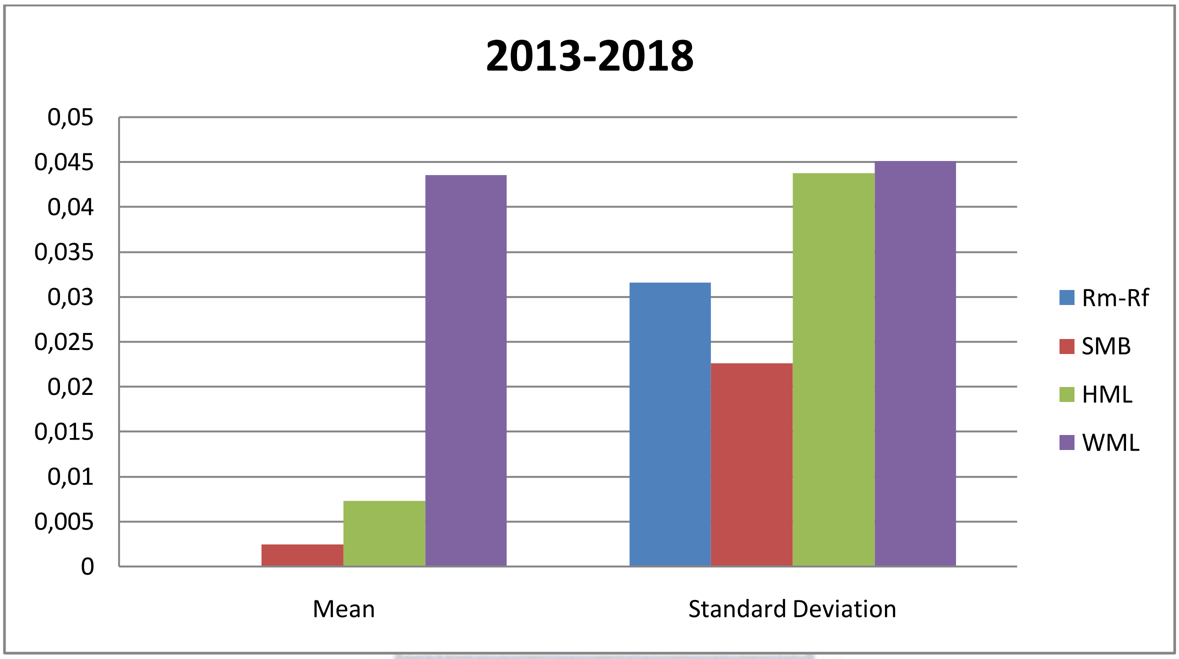
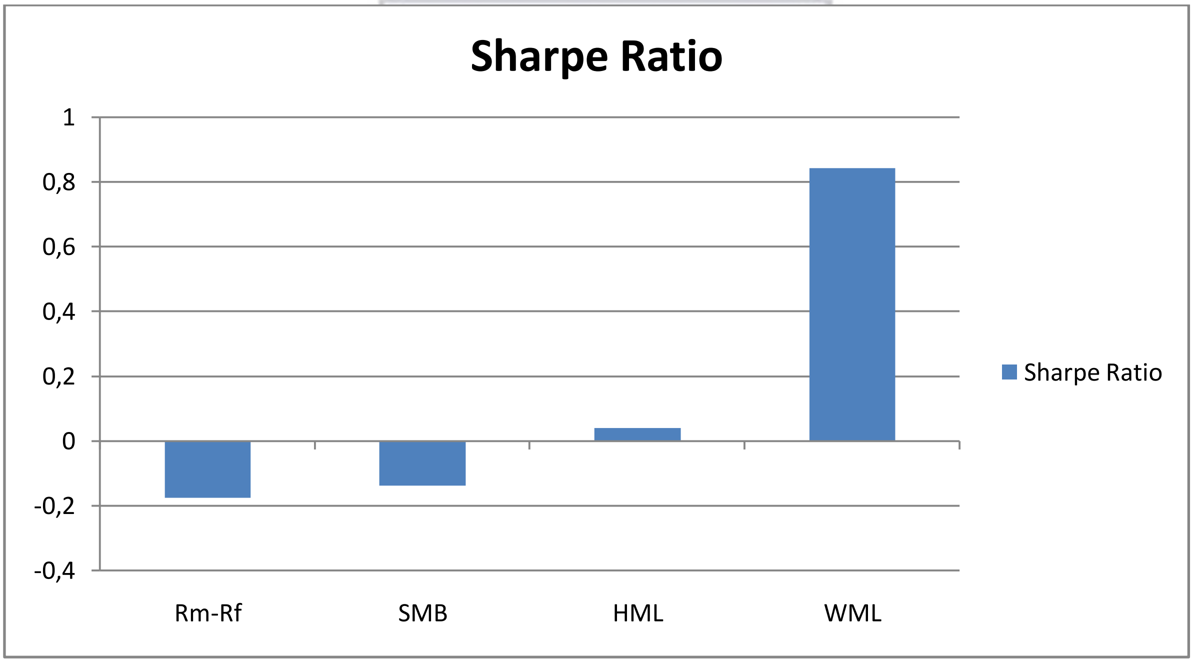


Figure 6.10: Sharpe Ratio of Factor Premiums over the Period 2013-2018



These differing results may stem from differences in datasets, as Krueger and Johnson (1991) and Bhardwaj and Brooks (1993) carry out their studies on the U.S. stock market. The divergences may equally stem from differences in examination periods. Indeed, Barnard and Bunting (2015), though their study focuses on the JSE, cover the period from 2006 to 2012 in their study, while the second downward period of this study focuses on the period from 2013 to 2018. It should be noted that the results from the first downward period (2007 - 2009) align with the findings by Barnard and Bunting (2015) with regard to the behaviour of the small-cap premium, thereby providing support to the possible reasons for discrepancies highlighted above.

Interestingly, the value premium instead falls from 1.65% in the first downward period to 0.73% in the second one. Furthermore, the premium is larger in 2013 – 2018 than in 2002 – 2007 (0.25% per month on average) and 2009 – 2013 (-2.03% per month on average). In other words, the HML portfolio generates larger premiums in downward periods than in upward periods, and the premium is even much larger in periods of financial crisis. This concurs with the variations in the magnitude of the value effect reported in Chapter 5 (sub-section 5.3.3.2,), and aligns with empirical evidence that the value premium tends to be larger during downward economic periods as compared to upward economic periods (for example, see Xing and Zhang, 2005; Kwag and Lee, 2006; and Athanassakos, 2009; among others).

Turning to the risks inherent to the style premiums, Table 6.5 and Figure 6.9 show that the highest standard deviation is related to the momentum premium (4.51%), followed by the value premium (4.37%). The small-cap risk premium exhibits the lowest standard deviation among all three style premiums (2.26%). The standard deviation for the market risk premium stands at 3.15%, higher than that of the small-cap premium, but lower than the other two style premiums. These observations suggest that during the period 2013 – 2018, the momentum premium is the riskiest premium, while the small-cap premium is the least risky one, and is even less volatile than the market risk premium.

According to Table 6.5 and Figure 6.10, the WML portfolio displays the best risk-adjusted performance over the period 2013 – 2018 since it delivers a Sharpe ratio of 0.8413, compared to HML portfolio's (0.039) and SMB portfolio's (-0.1382). The market portfolio equally yields a negative Sharpe ratio, equal to -0.1767. This means that when risk is accounted for, the WML portfolio still delivers the best performance, followed by the HML portfolio, whereas the SMB portfolio displays the worst performance among the three style portfolios. From a comparative point of view, the SMB and WML portfolios generate a better risk-adjusted performance in the period 2013 – 2018 than in the period 2007 – 2009 (Sharpe ratios of -0.6911 and 0.6491 respectively, see Table 6.4). Conversely, the HML portfolio's risk adjusted performance is better in the first downward period than in the second one (Sharpe ratio of 0.2704 in 2007 – 2009 compared to 0.039 in 2013 - 2018). These results may mean that the HML portfolio's risk-adjusted performance is stronger in a crisis period than in a typical downward phase of the business cycle on the JSE, while the reverse is true for the SMB and WML factor portfolios.

The above analysis of the style premiums over the various phases of the South African business cycle shows that the performance of the factor portfolios uncovered in the analysis over the whole study period (2002 - 2018) does not actually hold throughout the study period. Indeed, the premiums vary from one phase to another, and the direction of the movements tends to be similar for upward phases as well as for downward phases. In other words, they exhibit a cyclical behaviour on the JSE, and the variation trend, depending on the phase of the business cycle, provides a hint about the nature of their relationship with the business cycle in question.

6.4 Relationship of Style Premiums with the Business Cycle

The analysis in Section 6.3 above sheds light on the relationship between the size, value, and momentum premiums and the business cycle on the JSE over the period from 2002 – 2018.

More specifically, the small-cap premium is larger during the upward phases of the business cycle than during the downward phases. The largest small-cap premium (1.88% per month on average) is observed during the pre-2008 crisis period (2002 - 2007) when the South African economy experienced a significant expansion. Besides, the smallest premium (-1.15% per month on average) is reported for the period 2007 – 2009, which encompasses the 2008 financial crisis period. Thus, the small-cap premium increases when the economic cycle is in its upward phase, and decreases (and even turns negative) when the cycle experiences a downward phase. In other words, the small-cap premium is procyclical on the JSE. The findings are consistent with prior empirical evidence pertaining to the cyclicality of the small-cap premium on international markets and on the JSE, including Krueger and Johnson (1991), Bhardwaj and Brooks (1993), Perez-Quiros and Timmermann (2000), Kim and Burnie (2001), Barnard and Bunting (2015), Switzer and Pickard (2016), and Sarwar et al. (2017), among others.

With regard to the value premium, the analysis reveals that it is positive and large during downward phases, but negative or small during upward phases of the South African business cycle. Indeed, the smallest value premium (-2.03% per month on average) is reported in the second upward period (2009 - 2013), as the South African economy was recovering from the 2008 financial crisis. Conversely, the largest value premium (1.65% per month on average) is observed in the first downward period (2007 - 2009) encompassing the financial crisis episode. The results from the analysis of the value premium suggest that it rises when the South African economy is in a downward phase, and rises even further when the economy faces a crisis. Meanwhile, when the economy is booming, the premium reduces or vanishes completely. This signifies that the value premium is countercyclical on the JSE over the examination period. Most prior studies document a similar behaviour of the value premium, such as Krueger and Johnson (1991), Xing and Zhang (2005), Kwag and Lee (2006), Athanassakos (2009), Scheurle and Spremann (2010), and Gulen, Xing, and Zhang (2011), to name a few. However, few studies argue that the value premium is procyclical, such as Liew and Vassalou (2000) for U.S. and European markets, and Bayramov (2013) for European markets.

From the analysis in Section 6.3, it is noticed that the momentum premium remains positive throughout the various phases of the South African business cycle. Nevertheless, the premiums are larger in upward phases than in downward phases. The 2002 – 2007 upward period witnesses the largest momentum premium (5.24% per month on average) whereas the lowest premium (3.9% per month on average) is reported in the 2007 – 2009 downward period. Therefore, the momentum premium surges in upward phases of the business cycle and diminishes in downward phases. This means that the momentum premium is procyclical on the JSE over the study period. The evidence corroborates findings by earlier studies investigating the behaviour of the momentum premium, including Chordia and Shivakumar (2002), Cooper et al. (2004), Roh et al. (2014), and Daniel and Moskowitz (2016), among others. However, as with the value premium, few studies conclude otherwise as they find no evidence of the procyclical behaviour of the momentum premium, such as Liew and Vassalou (2000) and Sarwar et al. (2017).

Notwithstanding, these findings provide investors with valuable information with respect to the most profitable investment styles they should focus on, depending on the phase the business cycle is going through.

6.5 Conclusion

The objective of this Chapter, as outlined in Section 6.2, was to investigate on the one hand whether the size, value, and momentum premiums are cyclical on the JSE over the study period, and on the other hand whether the premiums vary in the same or opposite direction compared to the business cycle.

The analysis of the premiums generated by the size, value, and momentum factor portfolios (SMB, HML, and WML respectively) over the specific sub-periods corresponding to the phases of the South African economic cycle has uncovered interesting results. More specifically, the small-cap premium is positive and large during upward periods and negative or smaller during downward periods. Meanwhile, the value premium is negative or small during upward phases, but positive and larger during downward phases, and the largest premium is identified in the 2007 – 2009 period covering the 2008 financial crisis. Finally, the behaviour of the momentum premium is similar to that of the small-cap premium, except that it does not fall into negative territory in any sub-period. In other words, the style premiums are cyclical on the JSE, and the cyclical behaviour is more apparent around the 2008 financial crisis period.

These results support the bulk of prior empirical evidence that portfolios formed on size and momentum styles tend to perform better in economic expansions and bull markets than in economic recessions and bear markets, whereas portfolios formed on value style tend to exhibit better performances in periods of recession and crisis than in periods of expansion.

In addition, the analysis demonstrates that while the small-cap and momentum premiums vary in tandem with the trends in the business cycle, the value premium fluctuates in opposite directions to those of the business cycle. These observations suggest that the small-cap and momentum premiums are procyclical whereas the value premium is countercyclical, and these observations align with most findings uncovered on international markets identified earlier.

CHAPTER 7 – RISK-BASED NATURE OF SIZE, VALUE, AND MOMENTUM ON THE JSE

7.1 Introduction

Chapters 5 and 6 have uncovered on the one hand the presence of size, value, and momentum effects on the Johannesburg Stock Exchange (JSE), and on the other hand a cyclical behaviour of size, value, and momentum premiums over the period from 1 January 2002 to 31 December 2018. More specifically, size and momentum premiums tend to vary in the same direction as the trend in the business cycle (procyclical) whereas the value premium tends to fluctuate in an opposite direction to the trend in the business cycle (countercyclical). The evidence of style premiums being present on the South African stock market brings up the question of whether they arise as compensation for higher risk borne by investors or as a result of mispricing.

This chapter approaches the above question from a risk-based perspective as it examines whether size, value, and momentum premiums are driven by risk on the JSE over the examination period. The risk measure adopted in this chapter is beta, which measures the sensitivity of the movements in style premiums to movements in the market risk premium. In other words, beta measures the systematic risk embedded in the style premiums. Beta is obtained through a time-series regression of size, value, and momentum premiums on the market risk factor using the Capital Asset pricing Model (CAPM) over the full study period (2002 - 2018), and over the sub-periods corresponding to the various phases of the business cycle identified in the examination period and specified in Chapter 4 (see sub-section 4.2.1): two upward periods (2002 – 2007 and 2009 - 2013) and two downward periods (2007 – 2009, and 2013 - 2018). In addition, this chapter investigates whether small caps, value stocks, and winner stocks are riskier than large caps, growth stocks, and loser stocks respectively. In this regard, a comparative analysis of style portfolios' betas is carried out over the examination period and various sub-periods. Lastly, the performance of the style portfolios is compared using a risk-adjusted performance measure, the Treynor measure.

The chapter first briefly summarises previous literature pertaining to the rationale behind size, value, and momentum premiums both internationally and in South Africa, and provides a reminder of the chapter objectives (Section 7.2). The chapter then proceeds with the analysis of the CAPM regression results, focusing on the movements in beta over the study period (Section 7.3). The chapter ends with a comparative analysis of beta and Treynor measure of style portfolios constructed on size, B/M, and MOM12 portfolios over the study period (Section 7.4).

7.2 Chapter Objectives

The review of prior literature carried out in Chapter 3 (Section 3.5) uncovers an ongoing debate with respect to the rationale driving the size, value, and momentum premiums, with the main two ones cited being compensation for risk and mispricing. Indeed, international studies such as Fama and French (1992, 1993, and 1995), Liew and Vassalou (2000), Amihud (2002), Chordia and Shivakumar (2002), Peltomäki and Äijö (2015), Daniel and Moskowitz (2016), and Ruenzi and Weigert (2018), just to name few, contend that the style premiums mentioned above are demanded by investors to compensate them for bearing higher risk on the market. The studies cite various types of risk in this regard, such as macroeconomic risks (for example, Fama and French, 1992, 1993, and 1995; and Liew and Vassalou, 2000), liquidity risk (such as Amihud, 2002), volatility risk (for instance Peltomäki and Äijö, 2015; Daniel and Moskowitz, 2016), and crash risk (Ruenzi and Weigert, 2018) among others.

Conversely, a significant body of literature argues that size, value, and momentum premiums are driven by the irrational behaviour of investors (mispricing). For example, Hou and Moskowitz (2005) attribute the size premium to investors' underreaction, while, Lakonishok, Shleifer, and Vishny (1994) attribute the value premium to the overreaction of investors. Finally, Chan, Jegadeesh, and Lakonishok (1996) claim that the momentum premium is caused by the underreaction of investors to new and unexpected information. With regard to the South African market, the risk-mispricing debate tends to be overlooked. Thus, this chapter takes a risk-based stance as its main goals are:

- To investigate whether the size, value, and momentum premiums are compensation for risk on the JSE over the period from 1 January 2002 to 31 December 2018;
- To determine whether small caps are riskier than large caps, value stocks riskier than growth stocks, and past winners riskier than past losers, on the JSE over the examination period.

7.3 Analysis of Factor Premiums as Compensation for Risk

As highlighted above, the risk measure adopted in this chapter is beta, which is obtained through a time-series regression using the CAPM. The analysis starts with the regression results obtained over the full study period (2002 - 2018).

7.3.1 Full Period (2002 - 2018)

Table 7.1 below displays the CAPM regression results for the SMB, HML, and WML premiums over the period from 1 January 2002 to 31 December 2018.

Table 7.1: CAPM Regression Results of Average Monthly Style Premiums for the Period 2002-2018

Regression equation : $R_{Pt} - R_{ft} = \alpha_P + \beta(R_{mt} - R_{ft}) + e_{Pt}$			
	SMB	HML	WML
R^2	0.1523	0.0000	0.0094
p-value	0.0000***	0.9287	0.1686
Intercept	0.0092	-0.0003	0.0480
t-stat	4.3799	-0.1140	16.9516
p-value	0.0000***	0.9094	0.0000***
Beta (Rm-Rf)	-0.2785	-0.0050	-0.0864
t-stat	-6.0246	-0.0896	-1.3818
p-value	0.0000***	0.9287	0.1686
Note: *, **, and *** refer to 10%, 5%, and 1% level of significance respectively			

The coefficient of determination, R^2, which shows the proportion of the variations in factor premiums explained by the market risk premium, stands at 15.23% for the small-cap risk premium (SMB). This means that on average, 15.23% of the variations in the average monthly small-cap risk premium can be explained by movements in the market risk premium (MRP) over the period 2002 – 2018. The p-value of 0.000 signifies that the relationship is statistically significant at 1% level (extremely significant). Moreover, the R^2 for the value and momentum premiums (HML and WML respectively) equals 0 and 0.94% respectively, implying that the variations in the market risk premium account for less than 1% of variations in the two aforementioned factor premiums. However, the high p-values (0.9287 for HML and 0.1686 for WML) show that the results are not statistically significant.

The analysis of the intercept, also known as alpha or abnormal return, reveals that the SMB and WML portfolios outperform the market by 0.92% and 4.8% on average respectively, over the examination period. The t-statistics of the two factor portfolios being higher than absolute value of 2 (4.3799 for SMB and 16.9516 for WML) suggest that they perform better than the market in a consistent manner. With regard to the value factor portfolio, the intercept is negative and insignificant, suggesting that on average the latter underperforms the market but not consistently, over the period 2002 – 2018. These results support the findings in Chapter 6 (sub-section 6.3.1) that over the period 2002 – 2018, the SMB and WML factor premiums stand above the MRP whereas the HML factor premium is below the latter.

Beta, which measures the sensitivity of returns on the factor portfolios to movements in the returns on the market portfolio (proxied by ALSI), is negative for all three portfolios (size, value, and momentum factors), standing at -0.2785, -0.0050, and -0.0864 for SMB, HML, and WML respectively. This means that over the study period, the factor premiums tend to be negatively correlated to the market risk premium. Indeed, an analysis of the covariance between the market risk premium and the respective factor premiums reveals a negative correlation between the former and the latter. This may also mean that small caps, value stocks, and past winners tend to bear less systematic risk than their respective counterparts, namely large caps, growth stocks, and past losers. Nevertheless, the factor premiums are less volatile than the market risk premium as the absolute value of betas is less than 1. Besides, the relationship is extremely significant for SMB (p-value of 0.000) but statistically insignificant for HML and WML (p-values of 0.9287 and 0.1686 respectively).

The next sub-sections investigate whether the above relationships hold throughout the examination period, depending on the phases of the business cycle in which the analysis is performed.

7.3.2 Upward Periods (2002 - 2007 and 2009 - 2013)

Subsequent to the analysis of the systematic risk (proxied by beta) embedded in size, value, and momentum premiums over the full study period, an analysis of the aforementioned systematic risk is undertaken over the two upward phases of the business cycle identified in the examination period: the period from January 2002 to November 2007, and the period from September 2009 to November 2013.

7.3.2.1 Upward Period 2002 – 2007

The betas obtained through CAPM regressions of factor premiums on the market risk factor over the period 2002 – 2007 are presented in Table 7.2 below.

Table 7.2: CAPM Regression Results of Average Monthly Style Premiums for the Period 2002-2007

Regression equation : $R_{Pt} - R_{ft} = \alpha_P + \beta(R_{mt} - R_{ft}) + e_{Pt}$			
	SMB	HML	WML
R^2	0.1966	0.0036	0.0005
p-value	0.0000***	0.6183	0.8603
Intercept	0.0232	0.0030	0.0526
t-stat	5.0308	0.7815	10.3914
p-value	0.0000***	0.4372	0.0000***
Beta (Rm-Rf)	-0.3916	-0.0393	-0.0185
t-stat	-4.1086	-0.5005	-0.1767
p-value	0.0001***	0.6183	0.8603
Note: *, **, and *** refer to 10%, 5%, and 1% level of significance respectively			

The Table above shows that on average, systematic risk accounts for 19.66% of movements in the monthly small-cap risk premium during the pre-crisis period, and the relationship is statistically significant at 1% level (p-value = 0.0000). Conversely, only 0.36% and 0.05% of movements in the value premium and momentum premium respectively, are explained by the market risk premium. In addition, these relationships are statistically insignificant (p-value of 0.6183 for HML factor premium and 0.8603 for WML factor premium).

A comparative analysis of the R^2 values in Table 7.2 and Table 7.1 (full period) shows that the R^2 values are higher for SMB and HML in Table 7.2 (19.66% and 0.36% respectively) than in

Table 7.1 (15.23% and 0% respectively), while the reverse is true for WML (0.05% in Table 7.2 against 0.39% in Table 7.1). These variations in R^2 may mean that the level of exposure of factor premiums to market risk varies across time, implying that the factor premiums are partly compensation for risk embedded in the factor portfolios and borne by investors. Such inferences align with prior international studies, such as Fama and French (1992, 1993) who argue that size and value premiums reflect macroeconomic risks influencing average returns on the market.

Looking at the intercepts of the regressions (alphas or abnormal returns), it is noticed that SMB, HML, and WML factor portfolios outperform the market over the period 2002 – 2007, as the intercepts are positive for all three portfolios. However, SMB's and WML's alphas are statistically significant (t-statistics higher than absolute value of 2 for both) while HML's alpha is not (t-statistic = 0.7815). In other words, the two former portfolios consistently outperform the market over the pre-crisis period whereas the latter does not.

The 3 factor premiums exhibit negative betas over the period 2002 – 2007, standing at -0.3916 for SMB, -0.0393 for HML, and -0.0185 for WML. Just as observed in Table 7.1, these negative betas may signify that the factor premiums are negatively correlated to the market premium over the period, or that small caps, value stocks, and growth stocks, are less risky than large caps, growth stocks, and loser stocks respectively. Notwithstanding, the relationship is strong for SMB (statistically significant at 1% level), but weak for HML and WML (statistically insignificant).

It should be noted that except for WML, SMB's and HML's betas are higher in absolute value terms over the 2002 – 2007 period (Table 7.2) than over the full period (Table 7.1), amounting to -0.3916 and -0.0393 in Table 7.2 versus -0.2785 and -0.0050 in Table 7.1, respectively. Conversely, WML beta equals to -0.0185 for 2002 - 2007 period and -0.0864 for the 2002 – 2018 period. As mentioned in Chapter 6 (sub-section 6.3.2.1), the lower betas observed over the full study period may stem from the smoothing effect of the longer time period covering expansions, recessions, and crises.

7.3.2.2 Upward Period 2009 – 2013

Table 7.3 presents the regression results of the SMB, HML, and WML average monthly premiums on the market risk factor over the period from September 2009 to November 2013, using the CAPM regression equation.

Table 7.3: CAPM Regression Results of Average Monthly Style Premiums for the Period 2009-2013

Regression equation : $R_{Pt} - R_{ft} = \alpha_P + \beta(R_{mt} - R_{ft}) + e_{Pt}$			
	SMB	HML	WML
R^2	0.3670	0.1493	0.0604
p-value	0.0000***	0.0051***	0.0821*
Intercept	0.0100	-0.0227	0.0508
t-stat	4.0550	-7.0659	12.8990
p-value	0.0002***	0.0000***	0.0000***
Beta (Rm-Rf)	-0.3419	0.2460	-0.1825
t-stat	-5.3296	2.9324	-1.7753
p-value	0.0000***	0.0051***	0.0821*
Note: *, **, and *** refer to 10%, 5%, and 1% level of significance respectively			

The SMB factor portfolio exhibits the highest R^2, standing at 36.7%, while the R^2 for HML and WML factor portfolios stand at 14.93% and 6.04% respectively. In other words, over the period 2009 – 2013, 36.7%, 14.93%, and 6.04% of movements in the small cap, value, and momentum premiums respectively, are accounted for by market risk. Besides, the relationship is strong as R^2 is statistically significant for all three factor premiums (at 1% level for small-cap and value premiums, and at 10% level for momentum premium).

It is interesting to note that the explanatory power of the market risk factor in the period 2009 – 2013 is stronger than in the period 2002 – 2007, as displayed in Table 7.2. For example, the R^2 value for the SMB premium in Table 7.2 is equal to 19.66% compared to 36.7% in Table 7.3. Similarly, HML's and WML's R^2 values are equal to 0.36% and 0.05% in Table 7.2, compared to 14.93% and 6.04% respectively in Table 7.3. Lastly, only the R^2 value for SMB is statistically significant in the period 2002 – 2007 (Table 7.2), whereas it is significant for SMB, HML, and WML in the period 2009 – 2013. These results may suggest that the factor premiums under analysis are more sensitive to systematic risk during recovery periods as compared to expansionary periods, and might therefore imply that they arise partly as compensation for systematic risk embedded in average stock returns. This perspective aligns with prior empirical evidence on international markets. For instance, Fama and French (1992, 1993) and Liew and Vassalou (2000) contend that size and value premiums compensate for macroeconomic risks. Moreover, Chordia and Shivakumar (2002) advocate that momentum premium is caused by macroeconomic risks, while Peltomaki and Äijö (2015) and Daniel and Moskowitz (2016) argue that momentum premium might partly reward for volatility risk.

The intercepts of the regression presented in Table 7.3 are positive for SMB and WML, but negative for HML. This signifies that over the 2009 – 2013 period, SMB and WML factor portfolios outperform the market in a consistent manner, given their t-statistics higher than absolute value of 2 (4.0550 for SMB and 12.8990 for WML). Conversely, the performance of the HML portfolio is consistently below the performance of the market, as its p-value is equal to 0.0000. These observations confirm the results obtained in Chapter 6 (sub-section 6.3.2.2), whereby the value premium stands below the market risk premium, while the small-cap and the momentum premiums stand above the market risk premium.

With respect to systematic risk as proxied by beta, Table 7.3 displays a negative beta for the small-cap and the momentum premiums (-0.3419 and -0.1825 respectively), but a positive beta for the value premium (0.246). In other words, the two first factor premiums might be varying in opposite direction to the market while the last one is varying in tandem with the market over the period 2009 – 2013. More importantly, in absolute value terms, HML and WML betas are higher in 2009 – 2013 (0.246 and 0.1825, see Table 7.3) than in 2002 – 2007 (0.0393 and 0.0185 respectively, see Table 7.2). This may imply that these factor premiums are perceived as riskier during this upward period than during the previous one, which can be justified by the fact that the 2009 – 2013 period witnesses the aftermath of the 2008 global financial crisis and, consequently, investors are still fearful of the market. This also supports the inference made when analysing the R^2 values earlier that the premiums tend to be more sensitive to market risk during this period of economic recovery. However, the small-cap premium’s beta instead decreases between 2002 - 2007 and 2009 – 2013 in absolute value terms (0.3916 and 0.3419 respectively), and seems to contradict the above inference.

The analysis of CAPM regression results in upward periods of the business cycle suggests that size, value, and momentum premiums are more sensitive to systematic risk in certain periods than in others and, thus, tend to support prior international evidence that these premiums are rewards, at least in part, for risk inherent to the returns on these factor portfolios.

7.3.3 Downward Periods (2007 - 2009 and 2013 - 2018)

Subsequent to the analysis of the sensitivity of small-cap, value, and momentum premiums to movements in the market risk premium during upward phases of the South African business cycle, this chapter then examines the above in the downward phases, starting with the 2007 – 2009 period, which covers the 2008 financial crisis episode.

7.3.3.1 Downward Period 2007 – 2009

Table 7.4 presents a summary of the CAPM regression results of the monthly average factor premiums on the market risk factor over the period from December 2007 to August 2009.

The Table shows that systematic risk accounts for 27.57% of movements in the small-cap risk premium over the period 2007 – 2009, and the relationship is statistically significant at 5% level (p-value = 0.0145). Meanwhile, less than 5% of variations in the value and momentum premiums are explained by movements in the market risk premium (R^2 = 4.27% for HML and 4.11% for WML) over the same period, and the relationship is statistically insignificant (p-value of 0.369 for HML and 0.378 for WML).

Table 7.4: CAPM Regression Results of Average Monthly Style Premiums for the Period 2007-2009

Regression equation : $R_{Pt} - R_{ft} = \alpha_P + \beta(R_{mt} - R_{ft}) + e_{Pt}$			
	SMB	HML	WML
R^2	0,2757	0,0427	0,0411
p-value	0,0145**	0,3690	0,3780
Intercept	-0,0139	0,0155	0,0374
t-stat	-2,5314	2,2705	3,5494
p-value	0,0203***	0,0350**	0,0021***
Beta (Rm-Rf)	-0,1985	-0,0839	-0,1276
t-stat	-2,6894	-0,9202	-0,9026
p-value	0,0145**	0,3690	0,3780
Note: *, **, and *** refer to 10%, 5%, and 1% level of significance respectively			

A comparative analysis reveals that the R^2 values for the period 2007 – 2009 are higher than observed in the first upward period (2002 - 2007) but lower than observed in the second one (2009 - 2013), which may imply that at the climax of the 2008 global financial crisis, the factor premiums were more sensitive to market risk as compared to 2002 – 2007, but less sensitive to market risk as compared to 2009 – 2013 on the JSE, other types of risk being at play.

For instance, empirical studies on international markets such as Perez-Quiros and Timmermann (2000), Hwang, Min, McDonald, Kim, and Kim (2010), and Sarwar, Mateus, and Todorovic (2017) contend that the small-cap premium compensates for credit risk inherent to small stocks. Besides, Ruenzi and Weigert (2018) carry out a study on 23 international markets over the period 1963 – 2012 (covering the 2008 global financial crisis period) and assert that the momentum premium rewards for exposure to crash risk on the market (though they do not exclude a behavioural explanation for the momentum effect).

The intercepts of the regression in Table 7.4 reveal that over the 2007 – 2009 period, the SMB factor portfolio underperforms the market while the HML and WML outperform the market, and the portfolio performances are consistent as all the intercepts are statistically significant at 1% and 5% levels. These findings align with the results presented in Chapter 6 (sub-section 6.3.3.1), showing that the SMB portfolio exhibits a negative premium while the HML and WML portfolios enjoy positive premiums.

The small-cap, value, and momentum premiums all load negatively on the market risk factor over the period 2007 – 2009, and the factor loading is statistically significant at 5% level for SMB (p-value = 0.0145) and is statistically insignificant for HML and WML (p-value of 0.369 and 0.378 respectively). In absolute value terms, the betas are lower in the period 2007 – 2009 (Table 7.4) than in the period 2009 – 2013, but higher than in the period 2002 – 2007, which supports the earlier observation that the sensitivity of the factor premiums to systematic risk vary from one phase of the business cycle to the other one. Lastly, the negative betas may be a hint that, just as observed in the period 2002 – 2007, small caps, value stocks and past winners are less risky than large caps, growth stocks, and past losers respectively, over the period 2007 – 2009.

7.3.3.2 Downward Period 2013 – 2018

For the downward period December 2013 – December 2018, the regression results using the CAPM are displayed in Table 7.5 below.

From Table 7.5, it is observed that the R^2 of the small-cap premium stands at 22.13%, which means that 22.13% of fluctuations in the small-cap risk premium are accounted for by the market risk factor, and the relationship is statistically significant at 1% level (p-value of 0.0001). With respect to HML and WML, the R^2 is equal to 1.1% and 2.1% respectively, meaning that less than 3% of variations in value and momentum premiums are explained by systematic risk over the period 2013 – 2018 on the JSE. In addition, the R^2 values are statistically insignificant (p-value of 0.4216 and 0.2647 for HML and WML respectively).

Table 7.5: CAPM Regression Results of Average Monthly Style Premiums for the Period 2013-2018

Regression equation : $R_{Pt} - R_{ft} = \alpha_P + \beta(R_{mt} - R_{ft}) + e_{Pt}$			
	SMB	HML	WML
R^2	0,2213	0,0110	0,0210
p-value	0,0001***	0,4216	0,2647
Intercept	0,0025	0,0073	0,0435
t-stat	0,9520	1,2964	7,5528
p-value	0,3450	0,1999	0,0000***
Beta (Rm-Rf)	-0,3370	0,1453	-0,2075
t-stat	-4,0945	0,8093	-1,1260
p-value	0,0001***	0,4216	0,2647
Note: *, **, and *** refer to 10%, 5%, and 1% level of significance respectively			

Besides, the R^2 values in this second downward period are lower than those recorded in the first downward period (2007 - 2009). For instance, the R^2 value for the SMB premium is 27.57% in the first downward period (Table 7.4), but falls to 22.13% in the second downward period (Table 7.5). A similar drop in the coefficient of determination is observed for HML and WML across the two downward periods. This signifies that on average, the factor premiums are less sensitive to systematic risk in the post-recovery period (2013 - 2018) than in the financial crisis period (2007 - 2009).

The three factor portfolios outperform the market over the period 2013 – 2018, as Table 7.5 reports a positive alpha for all three portfolios. However, the abnormal return is statistically insignificant for SMB and HML, but statistically significant at 1% level for WML. These results align with the findings in Chapter 6 (sub-section 6.3.3.2) that the small-cap, value, and momentum risk premiums are higher than the market risk premium in the second downward period.

The SMB and WML factor portfolios exhibit negative betas (-0.34 and -0.21 respectively) whereas the HML factor portfolio displays a positive beta (0.15). The sensitivity to movements in the market risk premium is strong for SMB (p-value of 0.0001), but weak for HML and WML (p-value of 0.4216 and 0.2647 respectively). Moreover, the absolute values of betas in period 2013 – 2018 are higher than those observed during the period 2007 – 2009 (0.1985, 0.0839, and 0.1276 for SMB, HML, and WML respectively). This suggests that on the one hand, the exposure of the factor premiums to market risk varies as the economic conditions change; on the other hand they tend to be more sensitive to systematic risk in downward phases of the South African business cycle not induced by the financial crisis.

The analysis of the CAPM regressions of average monthly factor premiums (SMB, HML, and WML) on the market risk factor over the full examination period and various phases of the business cycle uncovers interesting, yet quite mixed, results. First, the variations in the betas of the factor premiums over the various sub-periods suggest that the sensitivity of factor premiums to systematic risk fluctuates throughout the period as business conditions change. Second, looking at the R^2 values, the results suggest that market risk partly explains the movements in factor premiums under investigation, even though their relatively low values imply that it is not the sole variable influencing the premiums, as demonstrated in Chapter 5 with the multifactor asset pricing models (see Section 5.4). These results then support earlier findings on international markets with respect to the risk-based rationale of size, value, and momentum premiums (see for example Fama and French, 1992, 1993; Liew and Vassalou, 2000; Chordia and Shivakumar, 2002; Cakici and Tan, 2014; Peltomäki and Äijö, 2015; Daniel and Moskowitz, 2016; and Ruenzi and Weigert, 2018).

However, as the portfolios exhibit a negative beta in certain sub-periods (2002 – 2007 and 2007 – 2009 for instance), this may mean that small caps, value stocks, and past winners bear less systematic risk than large caps, growth stocks, and past losers, respectively, over those periods, thus providing mixed conclusions regarding the risk-based explanation of size, value, and momentum premiums. This risk relationship among the style portfolios is further analysed in the next section.

7.4 Sensitivity of Style Portfolio Returns to Market Risk

As the analysis provided in the previous section suggests that size, value, and momentum premiums partly compensate for risk but with some mixed conclusions, this section investigates whether small caps, value stocks, and past winners are fundamentally riskier than large caps, growth stocks, and past losers respectively. In this regard, the mean, beta, and Treynor measure of the 6 portfolios used to construct the SMB, HML, and WML factor portfolios are computed and analysed over the full examination period, and over the various phases of the South African business cycle identified earlier. The 6 portfolios include: small-cap and large-cap portfolios, value and growth portfolios, past winners and past losers portfolios.

7.4.1 Full Period (2002 - 2018)

Table 7.6 below summarises the performance measures (mean, beta, and Treynor measure) of the aforementioned style portfolios over the period from January 2002 to December 2018.

Table 7.6: Performance Measures of Style Portfolios for the Period 2002-2018

	Small	Big	Value	Growth	Winners	Losers
Mean	0.0518	0.0441	0.0472	0.0475	0.0722	0.0247
Beta	0.5191	0.8002	0.6505	0.6492	0.6441	0.7299
Treynor Measure	0.0879	0.0473	0.0630	0.0636	0.1024	0.0252

Table 7.6 shows that over the period 2002 – 2018, the small-cap portfolio outperforms its large-cap counterpart on average on the JSE, as the average monthly return of the former stands at 5.18% versus 4.41% for the latter. Similarly, past winners outperform past losers on

average over the period, given the returns of the former of 7.22% against 2.47% per month on average, over the period. Conversely, the value portfolio slightly performs below the growth portfolio. Indeed, the monthly return of the value portfolio is equal to 4.72% whereas that of the growth portfolio is equal to 4.75%. The analysis of the returns on style portfolios used to build the factor premiums sheds light on the results reported in Table 6.1 and showing that the small-cap and momentum premiums are positive over the period 2002 – 2018 whereas the value premium is negative over the same period (see sub-section 6.3.1).

The analysis of the betas of the 6 style portfolios reported in Table 7.6 uncovers interesting results. More specifically, small caps and past winners exhibit a lower beta (0.5191 and 0.6441 respectively) than large caps and past losers (0.8002 and 0.7299 respectively). In other words, the portfolios of small stocks and past winners bear less systematic risk than the portfolios of big stocks and past losers. Conversely, the betas of the value and growth portfolios are quite close to each other, though the former is just slightly higher than the latter (0.6505 for value and 0.6492 for growth). This means that on average over the full study period, value stocks carry a slightly higher systematic risk than growth stocks on the JSE, which is in line with evidence from prior studies that value stocks are riskier than growth (see for instance Fama and French, 1995; Zhang, 2005).

A higher average return combined with a relatively lower beta leads to a higher Treynor measure for both small caps and past winners, as compared to large caps and past losers respectively. Indeed, the small-cap portfolio displays a Treynor measure of 0.0879 against 0.0473 for the big-cap portfolio. Similarly, while the past winners portfolio's Treynor measure is equal to 0.1024, the one for past losers portfolio equals a mere 0.0252. Lastly, the Treynor measures for both value and growth portfolios are not far from each other, though the latter's measure is slightly higher than the former's (0.0636 for growth against 0.063 for value). This signifies that on a risk-adjusted basis, small caps and past winners outperform large caps and past losers on average respectively, whereas value stocks slightly underperform growth stocks on average on the JSE over the period 2002 – 2007. It is worth noting that similar findings are reported in Chapter 6 (see sub-section 6.3.1, Table 6.1).

7.4.2 Upward Periods (2002 – 2007 and 2009 - 2013)

In order to establish whether the risk relationships observed above between small and large caps, value and growth stocks, and past winners and past losers hold throughout the full study period, a sub-period analysis is carried out starting with the two upward phases of the business cycle previously identified: the pre-2008 financial crisis period (January 2002 - November 2007) and the post-2008 crisis period (September 2009 – November 2013).

7.4.2.1 Upward Period 2002 – 2007

The performance measures of the 6 style portfolios under investigation for the period 2002 – 2007 are presented in Table 7.7 below.

Table 7.7: Performance Measures of Style Portfolios for the Period 2002-2007

	Small	Big	Value	Growth	Winners	Losers
Mean	0.0748	0.0560	0.0660	0.0635	0.0914	0.0390
Beta	0.4181	0.8138	0.6218	0.6631	0.6584	0.6763
Treynor Measure	0.1613	0.0598	0.0944	0.0847	0.1278	0.0469

According to the Table, small caps, value stocks, and past winners outperform large caps, growth stocks, and past losers respectively on the JSE over the pre-crisis period. For instance, the average monthly return on the small-cap portfolio is 7.48% against 5.6% for the big-cap portfolio. Likewise, the value and past winners portfolios exhibit average monthly returns of 6.6% and 9.14% respectively, against 6.35% and 3.9% for their respective counterparts. These results echo the findings reported in Table 6.2 in Chapter 6 which show that size, value, and momentum premiums are positive on the JSE for the period 2002 – 2007(sub-section 6.3.2.1).

As equally observed in Chapter 6 (sub-section 6.3.2.1), the levels of returns in the first upward period are higher than the levels observed over the full examination period. For example, the small cap portfolio's monthly return stands at 7.48% for the 2002 – 2007 period (Table 7.7) against only 5.18% for the full study period (Table 7.6). The lower return levels in the 2002 – 2018 period probably stem from the smoothing effect of the period which includes recession and crisis episodes.

The analysis of the exposure of the style portfolios to market risk (as measured by beta) indicates that the small-cap, value, and winners portfolios display a lower beta than large-cap, growth, and losers portfolios respectively. In other words, the former are less risky than the latter over the period from 2002 to 2007. These results contradict evidence from prior research regarding the risk exposures of style portfolios. For example, Fama and French (1992, 1993) argue that small stocks are less profitable than large stocks and, consequently, riskier. Also, Amihud (2002) contends that small caps are less liquid than large caps and, as a result, they are riskier. Fama and French (1992, 1993, and 1995) equally claim that value stocks are fundamentally riskier than growth stocks because value companies suffer a higher distress than growth companies. Meanwhile, Zhang (2005) advocates that value stocks tend to bear higher operating risk than growth companies. Lastly, Ruenzi and Weigert (2018) assert that past winners tend to face higher crash risk than past losers.

However, it should be noted that while exposure to market risk seems to contradict empirical evidence that small caps, value stocks, and past winners are riskier than large caps, growth stocks, and past losers respectively, firm-specific risks such as operating risk, when accounted for, might give a different outcome. For example, when looking at the standard deviation of small-cap and large-cap portfolios (which proxies for total risk - not reported here), it is observed that the former equals to 0.05 whereas the latter stands at 0.04. In other words, in total risk terms, small caps are riskier than large caps. Similarly, the standard deviation for past winners equals 0.048 against 0.044 for past losers. Nevertheless, the value portfolio displays a standard deviation slightly lower than the one of the growth portfolio (0.043 and 0.044 respectively).

In terms of risk-adjusted performance measures, Table 7.7 reveals that small, value, and past winner stocks yield higher Treynor measures (0.16, 0.09, and 0.12 respectively) than big, growth, and past loser stocks (0.06, 0.08, and 0.05 respectively) over the period 2002 – 2007. In other words, the highest premium per unit of market risk is generated by small caps while the lowest one is yielded by past losers. Nevertheless, the performance is superior to the average performance over the full study period (see Table 7.6).

7.4.2.2 Upward Period 2009 – 2013

Table 7.8 highlights the performance measures of the small-cap, value, past winners, large-cap, growth, and past losers portfolios for the period from September 2009 to November 2013.

Table 7.8: Performance Measures of Style Portfolios for the Period 2009-2013

	Small	Big	Value	Growth	Winners	Losers
Mean	0.0473	0.0407	0.0350	0.0552	0.0677	0.0188
Beta	0.3682	0.7041	0.6528	0.4121	0.4335	0.6109
Treynor Measure	0.1156	0.0511	0.0463	0.1225	0.1453	0.0229

It is apparent from Table 7.8 that while small-cap and past winners portfolios yield higher average monthly returns than large-cap and past losers portfolios, the value portfolio instead generates a lower return than the growth portfolio. Indeed, the average monthly returns reported in the Table for small-cap, value, and growth portfolios stand at 4.73%, 3.5%, and 6.77% respectively, against 4.07%, 5.52%, and 1.88% for big-cap, growth, and past losers portfolios respectively. In other words, small stocks and past winners outperform big stocks and past losers, whereas value stocks underperform growth stocks on the JSE over the period 2009 – 2013. This is in line with the results reported in Chapter 6 (sub-section 6.3.3.2) that while the small-cap and momentum premiums are positive over the same period, the value premium is negative. It further confirms the value effect reversal observed over the period 2009 – 2013 and documented in Chapter 5 (sub-section 5.3.2.2).

Nevertheless, the returns levels are lower on average compared to the first upward period. For instance, the small-cap portfolio in this sub-period displays a mean of 4.73% which is almost half of its mean in the first upward period. The remaining 5 portfolios equally experience significant drops in returns between the first and second upward period, probably due to the fact that the second sub-period follows the financial crisis period which wiped out a significant portion of the market value of stocks and, by the period 2009 – 2013, stock market value is not yet back to its pre-crisis levels.

Turning to betas displayed in Table 7.8, it is observed that the betas of the small-cap and winners portfolios (0.37 and 0.43 respectively) are lower than the betas reported for large-cap and losers portfolios (0.7 and 0.61 respectively). On the contrary, the value portfolio exhibits a higher beta (0.65) than its growth counterpart (0.41). This means that in terms of systematic risk, small stocks and past winners tend to be less risky than big stocks and past losers, but value stocks are riskier than growth stocks over the period 2009 – 2013 on the JSE. Again, these results are mixed as they partly corroborate prior evidence in the sense that value stocks are riskier than growth stocks, but contradict the evidence at the same time as small caps and past winners exhibit less risk than large caps and past losers.

Table 7.8 displays a higher Treynor measure for the small-cap and winners portfolios (0.12 and 0.15 respectively) as compared to the measure for large-cap and past losers portfolios (0.05 and 0.02 respectively). This signifies that the former yields higher returns per unit of market risk than the latter on the JSE over the post-crisis period. In other words, small-cap and winners portfolios continue to outperform their large-cap and losers counterparts when systematic risk is accounted for. With regard to value and growth portfolios, the reverse is observed as the Treynor measure for the value portfolio is lower than that of the growth portfolio (0.05 against 0.12), meaning that value stocks still underperform growth stocks even after accounting for systematic risk.

The above analysis of the systematic risk embedded in the returns on style portfolios provide inconclusive results as to whether small caps, value stocks, and past winners are riskier than large caps, growth stocks, and past losers respectively during the various upward phases of the business cycle. The next step in the analysis focuses on the risk relationship between these style portfolios in the downward phases of the business cycle.

7.4.3 Downward Periods (2007 – 2009 and 2013 - 2018)

The downward phases the analysis in this sub-section focuses on include the financial crisis period (December 2007 - August 2009), and the post-recovery period (December 2013 – December 2018)

7.4.3.1 Downward Period 2007 – 2009

The mean, beta, and Treynor measure of the small-cap and big-cap portfolios, value and growth portfolios, and past winners and losers portfolios for the period 2007 – 2009 are summarised in Table 7.9 below.

Table 7.9: Performance Measures of Style Portfolios for the Period 2007-2009

	Small	Big	Value	Growth	Winners	Losers
Mean	0.0265	0.0380	0.0388	0.0223	0.0575	0.0185
Beta	0.6009	0.7927	0.6049	0.6839	0.6586	0.7790
Treynor Measure	0.0304	0.0376	0.0506	0.0206	0.0748	0.0132

According to the Table, the small-cap portfolio underperforms the big-cap portfolio over the period 2007 – 2009, as their respective average monthly returns stand at 2.65% and 3.8%. Conversely, the value and winners portfolios outperform their growth and losers counterparts. The average monthly returns for value and growth portfolios are 3.88% and 2.23% respectively, and for winners and losers portfolios 5.75% and 1.85% respectively. It should be noted that similar findings are highlighted in Chapter 6 (sub-section 6.3.3.1) whereby a reversal of the size effect is observed, while value and momentum factor portfolios yield positive premiums. However, as the 2007 – 2009 period covers the 2008 global financial crisis episode, the average monthly returns on the 6 style portfolios are lower than those reported in the 2002 – 2007 period.

Interestingly, the betas of the small-cap, value, and winners portfolios (0.6, 0.6, and 0.66 respectively) are lower than the betas of their respective counterparts, big-cap, growth, and losers portfolios (0.79, 0.68, and 0.78 respectively). In other words, the former style portfolios bear less market risk than the latter style portfolios during the financial crisis period and, consequently, support the earlier CAPM results revealing negative betas for size, value, and momentum premiums over the same period (see sub-section 7.3.3.1).

A comparative analysis of the betas between 2002 – 2007 and 2007 – 2009 reveals that while small caps tend to be riskier in turbulent times (beta of 0.41 in the first sub-period against 0.6 in the second one), large caps tend to be less risky (beta of 0.81 in 2002 – 2007 against 0.79 in 2007 – 2009). Meanwhile, the value portfolio reveals to be less risky in 2007 – 2009 (beta = 0.6) than in 2002 - 2007 (beta = 0.62), whereas the systematic risk of the growth portfolio increases (0.66 in the first sub-period against 0.68 in the second one). Lastly, the beta of the winners portfolio remains unchanged across both periods at 0.66, while the losers portfolio becomes riskier (0.68 in 2002 – 2007 against 0.77 in 2007 - 2009). These findings may imply that investors would prefer large caps, value stocks and winners over small caps, growth stocks and losers during periods of financial crisis, thereby echoing the results from prior studies such as Kwag and Lee (2006) who assert that the value strategy should be adopted during crisis periods, and Peltomäki and Äijö (2015) who suggest that the momentum strategy might be more suitable during crisis periods as a backup investment style.

Unsurprisingly, Table 7.9 shows that the small-cap portfolio underperforms the large-cap portfolio even when systematic risk is controlled for. Indeed, the Treynor measure of the small-cap portfolio equals 0.03 whereas the one for the large-cap portfolio is 0.038 for the 2007 – 2009 period. On the contrary, value and past winners portfolios display higher Treynor measures than growth and past losers respectively, meaning that the former perform better than the latter on a risk-adjusted basis, over the financial crisis period.

7.4.3.2 Downward Period 2009 – 2013

With regard to the second downward phase of the South African business cycle identified in the examination period, Table 7.10 below presents the descriptive statistics of the 6 portfolios under investigation.

Table 7.10: Performance Measures of Style Portfolios for the Period 2013-2018

	Small	Big	Value	Growth	Winners	Losers
Mean	0.0377	0.0352	0.0386	0.0313	0.0586	0.0150
Beta	0.4219	0.7582	0.6220	0.4703	0.5499	0.7552
Treynor Measure	0.0761	0.0391	0.0530	0.0547	0.0964	0.0125

The analysis of the means reported in the Table reveals that small caps, value stocks and past winners perform better than large caps, growth stocks, and past losers respectively over the sub-period. Indeed, the average monthly return for the small-cap portfolio stands at 3.77% against 3.52% for the large-cap portfolio; the monthly return for the value portfolio is 3.86% while the one for the growth portfolio is 3.13%. Finally, the winners portfolio displays an average monthly return of 5.86% against 1.5% for the losers portfolio. Thus, the results support the findings presented in Chapter 6 (sub-section 6.3.3.2) showing positive premiums for SMB, HML, and WML for the period 2013 – 2018.

Besides, from a comparative point of view, the portfolios' returns are higher on average than the ones reported in the first downward period (Table 7.9), but lower than those reported in the second upward period (Table 7.8). For instance, the average monthly return on the small-cap portfolio equals 3.77% over the period 2013 – 2018, 2.65% over the period 2007 – 2009 (Table 7.9), and 4.73% for the period 2009 – 2013 (Table 7.8). The value portfolio marks the exception as its average monthly return is higher in both downward periods than in the second upward period (3.88% in 2007 - 2009, 3.86% in 2013 – 2018, but 3.5% in 2009 - 2013). These findings result from the prevailing business conditions in the second downward period being much less harsh than in the first downward period. However, as the value effect is countercyclical (see Section 6.4), the returns on the value portfolio tend to be higher in the downward phases than in the upward phases, and tend to be even much higher in a period of financial crisis.

While the small-cap portfolio and the winners portfolio exhibits lower betas (0.42 and 0.55 respectively) than large-cap and losers portfolios (0.76 and 0.76), the value portfolio instead displays a higher beta (0.62) than the growth portfolio (0.47). In other words, over the period 2013 – 2018, value stocks are riskier than growth stocks and equally yield higher returns (3.86%) than growth stocks (3.13%), echoing again the findings by prior studies on international markets, such as Fama and French (1995), Xing and Zhang (2005), Chui, Titman, Wei, and Xie (2012), and Cakici and Tan (2014), among others. However, the size and momentum portfolios seemingly contradict the evidence provided by the value and growth portfolios.

In terms of risk-adjusted performance, the small-cap and winners portfolios' Treynor measures are higher than those of large-cap and losers portfolios. Conversely, the value portfolio performs at a slightly lower level than the growth portfolio (0.053 for value against 0.054 for growth). In other words, the value portfolio outperforms the growth portfolio on a risk-unadjusted basis, but underperforms the growth portfolio when systematic risk is controlled for. Meanwhile, the small-cap and winners portfolios keep outperforming large-cap and losers portfolios after adjusting for systematic risk. This may imply that the value effect is more sensitive to systematic risk than the size and momentum effects.

The analysis of the performance and risk relationship between small caps and large caps, value stocks and growth stocks, and winners and losers during the downward phases of the South African business cycle, uncovers mixed findings just like in the upward phases. For example, the value portfolio is shown to be less risky in the period 2007 – 2009, yet yields a higher average monthly return than the growth portfolio. But in the 2013 – 2018 period, the value portfolio is reported to bear a higher market risk than the growth portfolio, and to perform at a higher level than the latter. This raises the question of whether systematic risk, proxied by beta, is the most suitable risk measure to investigate the risk relationship between style portfolios.

7.5 Conclusion

This chapter aimed at establishing whether size, value, and momentum premiums are driven by risk on the JSE over the period of study. The chapter further aimed at investigating whether small caps, value stocks and past winners are riskier than large caps, growth stocks, and past losers respectively.

Using beta as measure of risk (proxy for systematic risk), the analysis of CAPM regressions of returns on small-cap, value, and momentum premiums on the market risk factor over the full study period and over the various phases of the South African business cycle, reveals that the sensitivity of the factor premiums to movements in the market risk premium tends to vary throughout the study period. More specifically, the sensitivity of the factor premiums to market risk tends to be higher during the 2009 – 2013 period than during the 2002 – 2007 period. Also, the factor premiums are shown to be more sensitive to market risk in the second downward period than in the first one (financial crisis period). Lastly, the findings show that during the financial crisis period, the premiums' betas are higher than in the first upward period, meaning that the sensitivity of the factor premiums to market risk increases in turbulent economic times. These findings suggest that size, value, and momentum premiums are partly driven by systematic risk, as their sensitivity to the latter increases dramatically in most volatile times. These results echo the findings by several prior studies on international markets which demonstrate that the aforementioned style premiums are, at least partly, compensation for risk.

The analysis pertaining to the risk relationship between small caps and large caps, value stocks and growth stocks, and winners and losers, provides less clear-cut results. Indeed, small caps perform better than large caps while bearing less systematic risk, except for the 2007 – 2009 period during which small caps underperform large caps while bearing lower risk. Meanwhile, value stocks perform better than growth stocks during the 2002 – 2007 period, but display lower market risk than the latter, while outperforming growth stocks and displaying higher risk in the post-recovery period (2013 - 2018). Lastly, winners consistently outperform losers through all the sub-periods, but are less risky than the latter. While these results provide some evidence that small caps and value stocks are riskier than large caps and growth stocks respectively and, therefore, corroborate prior empirical evidence, the momentum case seems to contradict the evidence, as well as the risk behaviour of portfolios constructed on size and value in some specific sub-periods.

These contrasting results may signal the existence of the low-beta anomaly on the JSE, whereby high-beta stocks tend to yield lower average returns than low-beta stocks. They may equally signify that beta, which proxies for systematic risk, is not the most appropriate measure of the risk relationship pertaining to portfolios constructed on size, value, and momentum styles on the JSE over the examination period.

CHAPTER 8 – CONCLUSION

8.1 Summary of Background Studies

Size, value, and momentum effects have drawn a lot of attention and have triggered numerous studies since they were first identified about forty years ago. They have been named anomalies because they are not accounted for in average stock returns by the famous Capital Asset Pricing Model (CAPM), which is an equilibrium model describing a linear relationship between systematic risk and return.

The development of the CAPM heavily rests on the Modern Portfolio Theory (MPT) of Markowitz (1952) which stipulates that investors, as they are rational and risk-averse, are better off if they invest in portfolios of risky assets diversified enough to exhibit minimum risk for a stated level of returns, or, maximum returns for a stated risk level, known as mean-variance-efficient portfolios. Sharpe (1964), Lintner (1965), and Mossin (1966) independently develop the CAPM, by assuming the existence of a risk-free asset on the market which, when combined with the mean-variance-efficient portfolio, reduces unsystematic risk to negligible levels and results in a linear relationship between systematic risk, which is undiversifiable, and stock returns.

A direct implication of the CAPM is that investors can only yield returns which are proportional to the risk incurred. In other words, the CAPM implies market efficiency. The concept of market efficient was developed in parallel to the CAPM, starting from the pioneering studies on the randomness of stock prices by Regnault (1863) and Bachelier (1900), followed by Kendall (1953) who popularises the random walk theory. Exploiting this theory, Fama (1970) takes the concept of efficient markets a step further to develop the Efficient Market Hypothesis (EMH). This Hypothesis posits that security prices rapidly incorporate new information arriving on the market so that they reflect the intrinsic value of the securities at all times. Fama (1970) further argues that tests on the validity of the EMH necessitate an equilibrium model such as the CAPM.

However, several studies as from the 1970s revealed that the linear relationship established by the CAPM between market risk and stock returns may not hold as there are patterns in stock returns not accounted for by the CAPM, with the most prominent ones being the size effect (Banz, 1981), the value effect (Basu, 1977), and the momentum effect (Jegadeesh and Titman, 1993). Some researchers attribute the presence of size, value, and momentum anomalies on the markets to style risks not explained by the CAPM, and design multifactor models to remedy the shortcomings of the latter, including the three-factor model of Fama and French (1993), and the four-factor model of Carhart (1997). On the contrary, other researchers view the existence of the anomalies as the result of the irrational behaviour of investors, either overreacting or underreacting to unexpected information (Debondt and Thaler, 1985, 1987; Lakonishok, Shleifer, and Vishny, 1994; among others).

This latter view, which falls under the umbrella of behavioural finance, finds its roots in the earlier works of psychologists who argue that people in general, and investors in particular, are prone to emotions and cognitive biases and are, therefore, not always rational in their decision-making. The acclaimed prospect theory of Kahneman and Tversky (1979) demonstrates that investors are inclined to irrational behaviour in their decision-making when they are uncertain about the outcome of their decisions. Besides, Tversky and Kahneman (1974, 1981), Lux (1995), Larrick and Boles (1995), and Gervais and Odean (2001), among others, report that emotional reactions such as overconfidence, herd behaviour, and regret aversion drive investors' decision-making on capital markets.

The developing interest in size, value, and momentum effects led researchers to conduct many other studies following the ones that first identified these effects, the main focus being to determine whether the effects persisted after they were initially reported, and whether they persisted in out-of-sample studies. Some notable studies in this regard include Fama and French (1992) who document the size and value effects in the U.S., Jegadeesh and Titman (2001) who confirm the existence of the momentum effect in the U.S. using extended data compared to their original study, and Fama and French (2012) who report the existence of size, value, and momentum effects on more than 20 international markets. In South Africa, a great deal of studies equally document the size, value, and momentum anomalies, including Fraser and Page (2000), van Rensburg (2001), Basiewicz and Auret (2009), Hoffman (2012), and Page and Auret (2018), among others.

As the CAPM failed to account for stock returns patterns induced by size, value, and momentum effects, alternative asset pricing models were proposed to explain these effects. Fama and French (1993) propose the three-factor model which adds two factors to the market risk factor of the CAPM, designed to capture the size and value effects. The model fails to explain the momentum effect (Fama and French, 1996), leading Carhart (1997) to introduce the four-factor model of asset pricing, which augments the three-factor model with a fourth factor accounting for the momentum effect. More recently, Fama and French (2015) suggest a five-factor model, which they claim to possess a stronger explanatory power than their original three-factor model. A large number of studies have tested the ability of the aforementioned asset pricing models to explain size, value, and momentum anomalies on international markets, including for example Bello (2008), Fama and French (2012), Choi (2017), Fama and French (2017), and Foye (2018). The JSE has equally witnessed several studies testing the suitability of the above models, though the volume of research is thinner and results are more mixed. Some notable studies embody Basiewicz and Auret (2010), Mahlophe (2015), Boamah (2015), and Small and Hsieh (2017).

As some empirical evidence claimed the disappearance or attenuation of size, value, and momentum effects on capital markets (for example, see Schwert, 2003; Auret and Cline, 2011; and Cotter and McGeever, 2018), several studies have been carried out to determine whether these style effects are subject to cyclical trends, which would explain why they are weaker or inexistent in certain periods. Empirical findings uncovered by studies such as Krueger and Johnson (1991), Bhardwaj and Brooks (1993), Liew and Vassalou (2000), Kim and Burnie (2001), Xing and Zhang (2005), Kwag and Lee (2006), and Daniel and Moskowitz (2016), among others, actually reveal a cyclical behaviour on the part of size, value, and momentum premiums on international markets. South African studies on the subject matter, though scarce, reach a similar conclusion for the most part, with most notable studies including Graham and Uliana (2001), Hodnett (2014), Hsieh (2015), and Barnard and Bunting (2015). Lastly, most of the above empirical evidence suggests that the size and momentum premiums are procyclical, whereas the value premium is countercyclical.

The everlasting debate with respect to the cause of size, value, and momentum premiums being observed on capital markets equally inspired a lot of research on international markets. Proponents of the risk-based explanation to market anomalies contend that the style premiums reflect compensation for additional risk borne by investors, and this additional risk comes in many forms, such as macroeconomic risk (Fama and French, 1993), distress risk (Fama and French, 1995), liquidity risk (Amihud, 2002), volatility risk (Peltomäki and Äijö, 2015), and crash risk (Ruenzi and Weigert, 2018), to name but a few. Conversely, proponents of a behavioural-based explanation attribute the premiums to mispricing caused by the irrational behaviour of investors, and mostly cite overreaction and underreaction as the main behavioural patterns driving the premiums (see for instance Lakonishok, Shleifer, and Vishny, 1994; Daniel, Hirshleifer, and Subrahmanyam, 1998, 2001; Hou and Moskowitz, 2005; Hwang and Rubesam, 2013; and Chen and Shin, 2016). Unfortunately, no study on the JSE addressing this debate specifically has been found at the time of writing this thesis.

Thus, the mixed conclusions pertaining to the existence of size, value, and momentum effects on the JSE, the limited volume of studies on the cyclicality of the style premiums (with inconclusive findings), and the lack of studies addressing the risk/mispricing argument all motivated this study.

The study covers the period from 1 January 2002 to 31 December 2018, and uses as sample the common stocks of companies included in the FTSE/JSE All-Share Index (ALSI) which, after adjustments such as exclusion of companies with missing or insufficient data, results in a final sample of 208 companies. Since the study aims at investigating the cyclicality of size, value, and momentum effects on the JSE, the examination period is broken down into two business cycles, as determined by the SARB's 2018 quarterly bulletin, which are in turn broken into 2 phases each. This results in two upward phases (January 2002 – November 2007, and September 2009 – November 2013) and two downward phases (December 2007 – August 2009, and December 2013 - December 2018).

The construction of the portfolios necessary to test the existence of size, value, and momentum anomalies on the JSE, as well as the explanatory power of the Fama-French three-factor and five-factor model, and Carhart four-factor model, follows the methodology of Fama and French (1993) for portfolios based on size and B/M, Fama and French (2015) for portfolios based on operating profit and asset growth, and Boamah (2015) for portfolios sorted on size and momentum. Tests on the cyclicality of the style portfolios are carried out using performance evaluation measures, namely mean, standard deviation, and Sharpe ratio, whose fluctuations are analysed over the different phases of the business cycle previously specified Finally, in order to test the risk-based explanation of the style effects on the JSE over the period of study, variations in the betas of the factor portfolios replicating the behaviour of the size, value, and momentum premiums, are analysed. Beta is obtained through CAPM time-series regressions of average monthly factor premiums on the market risk factor over the different phases of the South African business cycle.

8.2 Summary of Key Findings

The analysis of the average monthly excess returns on test portfolios formed on size and B/M, and size and MOM12, and reported in Chapter 5, reveals the existence of the size, value, and momentum effects on the JSE over the full examination period (2002 - 2018). Indeed, monthly excess returns decrease from small-cap to large-cap portfolios in B/M and MOM12 segments, while they increase from low-B/M to high-B/M portfolios (except in the small-cap segment). Meanwhile, monthly excess returns rise monotonically from loser to winner portfolios in all size segments. The evidence of these style effects on the JSE aligns with findings from prior studies on both international and South African markets, including for example Fama and French (1992), Jegadeesh and Titman (1993, 2001), Basiewicz and Auret (2009), Fama and French (2012), Hoffman (2012), Hsieh (2015), and Page and Auret (2018).

However, the sub-period analysis pertaining to the style effects is more insightful. More specifically, the size effect and the value effect are stronger during the first upward phase (2002 - 2007) than during the second one (2009 - 2013), which is probably explained by the fact that the second period was more of a recovery period since the economy was just emerging from the 2008 global financial crisis. On the contrary, a reversal of the value effect is observed in the second upward period, as growth stocks outperform value stocks.

Interestingly, value stocks outperform growth stocks in both downward periods (2007 – 2009 and 2013 - 2018), and the value-growth spread is even larger during the first downward period, which coincides with the global financial crisis. These results echo prior findings which assert that the value effect tends to be stronger during crisis periods (see for example Kwag and Lee, 2006). Meanwhile, the size effect vanishes during the 2007 – 2009 downward period, and diminishes significantly during the 2013 - 2018 period as compared to the first upward period, thereby supporting earlier evidence of the disappearance/attenuation of the size effect, uncovered by researchers such as Schwert (2003) and Auret and Cline (2011). Lastly, the momentum effect is reported in both downward periods, but it is weaker than in the first upward period.

The analysis of the results from time-series regressions demonstrates that while the CAPM fails to capture the size, value, and momentum effects on the JSE, the Fama-French three-factor model (FF3F) does a good job in this regard, given its stronger explanatory power as compared to the CAPM's. Indeed, the R^2 values reported for FF3F regressions are much higher than the ones reported for the CAPM regressions. However, the FF3F seems not to account for the momentum effect, unlike the Carhart four-factor model (C4F), which exhibits higher R^2 values than FF3F for portfolios formed on momentum, clearly demonstrating a stronger explanatory power than the latter. Finally, the Fama-French five-factor model (FF5F) tends to be a more accurate predictor of stock returns on the JSE than the FF3F, aligning with Fama and French (2015) in the U.S. and Mahlophe (2015) in South Africa. Yet, results suggest that the FF5F may fail to explain the momentum effect on the JSE and, therefore, echo similar evidence by Fama and French (2016) in the U.S.

Turning to the cyclicality of size, value, and momentum effects discussed in Chapter 6, the analysis of the average monthly premiums on factor portfolios replicating the size effect (SMB), the value effect (HML), and the momentum effect (WML) uncovers results similar to those of previous empirical studies. As a matter of fact, the small-cap risk premium and the momentum risk premium are positive across the two upward periods embedded in the study period, even though the premiums are smaller in the second period (2009 - 2013) than in the first one (2002 - 2007). As observed in Chapter 5, these differences are likely due to the 2008 financial crisis that weakened the performance of style portfolios in the second period, which is more similar to a recovery period. Nevertheless, the positive premiums support findings by studies such as Krueger and Johnson (1991), Kim and Burnie (2001), Chordia and Shivakumar (2002), and Cooper, Gutierrez, and Hameed (2004).

With respect to the value effect, the value risk premium is positive for the pre-crisis period (2002 - 2007), but negative for the post-crisis period (2009 - 2013). Though the second part of the results contradicts most empirical evidence which shows that value stocks outperform growth stocks during expansionary periods (for example Athanassakos, 2009), it may be explained by the recovery state of the South African economy during that period.

However, the HML portfolio yields positive premiums for both downward periods, and the premium reported in the 2007 – 2009 period (including the financial crisis episode) is much larger than the one reported in the 2002 – 2007 (expansionary period). In other words, these results back up evidence by Krueger and Johnson (1991), Xing and Zhang (2005), Gulen, Xing, and Zhang (2011), and Barnard and Bunting (2015) that value stocks yield higher returns that growth stocks during periods of contraction. In addition, Kwag and Lee (2006) assert that the value premium is even larger during contractionary periods as compared to expansionary periods. Meanwhile, the small-cap premium becomes negative during the first downward period, and is close to zero during the second one, while the momentum portfolio stays positive in both periods, but is significantly smaller than during the upward periods. These findings suggest that the style premiums are indeed prone to a cyclical behaviour on the JSE. More specifically, small-cap and momentum premiums tend to vary in the same direction as the trend in the South African business cycle (procyclical), whereas the value premium tends to vary in the opposite direction (countercyclical).

The findings presented in Chapter 7, which addresses the risk/mispricing debate of size, value, and momentum anomalies from a risk-based perspective, accord with the results from most international studies, though the findings in this study are quite mixed. Using beta as the measure of risk (proxy for systematic risk), the analysis carried out shows that the betas of the small-cap, value, and momentum factor premiums vary from one phase of the South African business cycle to another, signifying that the sensitivity of the factor premiums to market risk is not constant over time. For example, the observation of the R^2 values from CAPM regressions reported for the financial crisis period (2007 - 2009) are higher than the values reported in the pre-crisis period, which corresponds to the 2002 – 2007 period. This suggests that during turbulent economic times, factor premiums are more exposed to systematic risk than during a booming economic period and, consequently, the premiums compensate, at least to an extent, for additional risk. Alternatively, this may imply that during expansionary periods, the factor premiums are less sensitive to systematic risk, but other risk patterns come into play. For example, Amihud (2002) cites liquidity risk as a possible explanation to the size premium; Zhang (2005) attributes the value premium to operating risk, while Daniel and Moskowitz (2016) point out volatility risk as the cause of the momentum premium.

The examination of the risk relationship between small stocks and big stocks, value stocks and growth stocks, and past winners and past losers, reveals that over the study period, large caps underperform small caps, but exhibit a higher exposure to market risk, except for the period covering the global financial crisis (2007 - 2009), during which large caps outperform small caps. Similarly, value stocks outperform growth stocks but bear lower risk during the first upward period (2002 - 2007), whereas they exhibit higher risk in the 2013 – 2018 period. With respect to winners and losers, the former outperform the latter throughout the examination period, but with lower systematic risk. In other words, the findings give some credit to the assertion that small caps and value stocks are riskier than large caps and growth stocks respectively to some extent, yet the momentum case contradicts the above assertion. The resulting inferences include the probable existence of the low-beta anomaly on the JSE, and the legitimate question of whether beta is the most suitable measure of risk with respect to analysing the risk relationship between style portfolios on the JSE.

8.3 Limitations of the Study and Suggestions for Further Research

The investigation of the cyclicality of size, value, and momentum effects on the JSE in this study relied on the phases of the South African business cycle as specified by the SARB, following the identification of turning points through an analysis of the leading, lagging, and coincident business cycle indicators (see Chapter 4, sub-section 4.2.1). The main limitation with the SARB's approach to business cycle turning points is the delay in determining and publishing the turning points in question. For example, the publication of the leading indicator may occur up to 8 weeks subsequent to the month of reference, while the determination of turning points may take up to 2 years after the events that led to the turn. In other words, the business cycle analysis may not be optimal with respect to forecasting and decision-making. Thus, subsequent research on cyclicality of style effects on the JSE should consider alternative indicators of business cycle turning points with stronger predictive power, such as the Business Confidence Index computed by the Bureau for Economic Research and the South African Chamber for Commerce and Industry. Also, future research in this area should consider other measures of economic performance such as earnings cycles or regime shifts, as this may provide new insights into the performance of the aforementioned investment styles on the JSE over time.

Another suggestion for possible future research addressing the rationale behind the size, value, and momentum effects on the JSE is the use of alternative risk measures to beta. For example, the South African volatility index (SAVI) could be used to assess the sensitivity of the style premiums to changes in volatility risk. It should be noted that the choice of beta over the SAVI in this study was motivated by the unavailability of SAVI data prior to 2007 when the index was launched, given that the examination period of this study starts about 5 years back (1 January 2002).

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