STYLE INVESTING AND INFORMATION CONVEYED BY PAST RETURNS IN SOUTH AFRICA:

AN EMPIRICAL ANALYSIS

This thesis is submitted in fulfilment of the requirements for the Degree of Master of Commerce in Finance.

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DECLARATION

I, Sthabiso Tarrence Mkwanazi, hereby declare that:

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ABSTRACT

The aim of this study was to establish the long-run relationship between six selected South African indices (i.e., large cap, small cap, resources, value, growth and industrials). Long-run relationships were analyzed in relation to mutual funds' style drift in an attempt to view the underlying diversification opportunities and potential risk faced by investors. The Engle-Granger two-step procedure and asset class factor models were used to encounter this territory. Using daily and weekly closing prices from 2006 to 2014 the results from the Engle-Granger two-step procedure show that there are drastic changes in long-run relationships between the six selected indices when broken into two year periods. In addition, the results reveal that a vast number of long-run relationships were established during the 2007 global financial crisis which indicates low diversification strategies during that period. The study captured a consistent, growing long-run relationship between three pairs of indices when the roll-over strategy was implemented. These pairs are small caps/ industrials, small caps/ large caps and small caps /value.

The results from the asset class factor model show that there were two apparent style drifts and abundant stock picking in the period covered. However, the reported stock picking does not harm diversification properties since managers ensure that their moves are against binding long-run relationships. Furthermore, the results from the asset class factor model reveal that fund managers tend to follow one another's moves. This is solid proof and confirmation of herding behaviour among fund managers. South African growth and value indices show complementary relationships when the literature pronounces them as substitutes. The literature declares them to be the opposite of each other. This study found that the growth and value indices possess strong positive linear relationships which are in contrast to what is documented in the literature.

Changes in long-run relationships and dispersed asset allocations have direct implications for investors' opportunities for diversification. Since positive long-run relationships erode diversifying properties, it is important to continue checking the long-run relationships between indices before investing as they are prone to drastic change in a short period of time, i.e., as little as two years.

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CHAPTER 1: INTRODUCTION

1.1 Introduction

Unit trusts or mutual funds, as they are commonly referred to, have witnessed phenomenal growth over the past three decades primarily driven by surplus liquidity in most world economies. Individual and institutional investors have favoured mutual funds as they offer diversification benefits even when small amounts are invested and, hence, offer a better opportunity to grow investment returns than could be achieved at household level. Furthermore, the amount of starting capital and technology required for unit trusts are not as demanding as for other investments or many other businesses (Njeri, 2012). Mutual funds consequently use these less restrictive requirements and returns as a carrot to lure investors and, in doing so, invest in 'styles' premised on the fund's investment philosophy. The unit trust industry is regulated and is hence regarded as a safe investment vehicle.

The question that arises is whether these mutual funds maintain their investment promise to deliver superior returns through consistently holding stocks that fit with the fund's investment style or if they stray into other styles over time – a phenomenon referred to as style drifting.

Mutual funds can be simply described as a collection of securities, monies, stocks and bonds from the public and private sectors with the aim of creating a large pool of wealth. Scholars like Pástor and Stambaugh (2002) and Chen et al. (2013) define mutual funds as investment vehicles created with the purpose of pooling funds from different investors to invest in different asset classes. These funds, which are managed by highly qualified individuals, are known to have proper and skilled management. When individuals or corporations put money into mutual funds, these funds are combined with other funds from similar minded investors. This large pool of funds enables fund managers to adopt better investment strategies than could be achieved if everyone was investing their funds directly in the assets of their choice (Chen et al., 2013). This phenomenon is known as economies of scale.

According to Rouwenhorst (2004), mutual funds can be traced back to the second half of the eighteenth century in The Netherlands. The first fund was motivated by the need to provide a small group of investors with the means and opportunities of diversifying their investments. This was achieved by investing in other countries like South America, Australia Germany and Spain, to name but a few. The first mutual fund emerged in a well-developed capital market, the Amsterdam Exchange (Rouwenhorst, 2004). The number of mutual funds gradually increased in the eighteenth century when merchants and brokers learned how to broaden their investment opportunities. Mutual funds can be categorised in many different classes ranging from equity, to money market, bonds, mixed or absolute all-class.

Equity funds are a common form of mutual funds that contain common and preferred stock securities (Cornett and Saunders, 2008). Money market mutual funds (MMMFs) are defined as low volatility types of investments that invest in cash assets and debt securities with short term maturities and minimal credit risk (Agapova, 2010). Open-end mutual funds are funds that do not place a limit on the amount of shares that the fund can issue and have no maturity period. The supply of shares in the fund is not fixed but can increase or decrease daily with purchase and redemption of shares (Cornett and Saunders, 2008). As long as there is demand for the fund's shares, the fund manager will sell the shares to investors who require them, hence increasing the value of the funds' assets (Paramasivan and Subramanian, 2009). A closed-ended mutual fund trades as a listed public company. Upon creation, the fund initiates a public offering to raise capital, and shares have a fixed supply and maturity period (Paramasivan and Subramanian, 2009).

In 1929, there were an estimated 19 open-ended mutual funds and approximately 700 close-ended mutual funds across the globe (Rouwenhorst, 2004). Tough economic conditions and the 1929 stock market crash led to drastic change. A large number of closed-ended funds were wiped out and few open-ended funds managed to survive (Rouwenhorst, 2004). With the introduction of Securities Act in 1933 in the United States of America (USA), and the Securities Act of 1934 and Investment Company Act of 1940, this industry became more regulated and stable. The industry recovered and expanded in the early 1950s, with 100 open-ended mutual funds emerging in the USA alone. Growth has continued to the present (Huij, 2007) .

In South Africa, mutual funds are the organ of Collective Investment Schemes (CIS) which, in turn, are an important part of the Johannesburg Stock Exchange (JSE). The Association of Savings and Investment South Africa (ASISA) notes that this industry showed healthy growth from 2011Q1 to 2015Q1. It offers portfolio managers and investors a large choice when allocating funds. The ASISA 2013 annual report notes that the local CIS industry had doubled in size in five years. This suggests that investors have faith and trust in this industry. The report also notes that investors invested nearly R1.5 trillion in the local CIS during 2013.

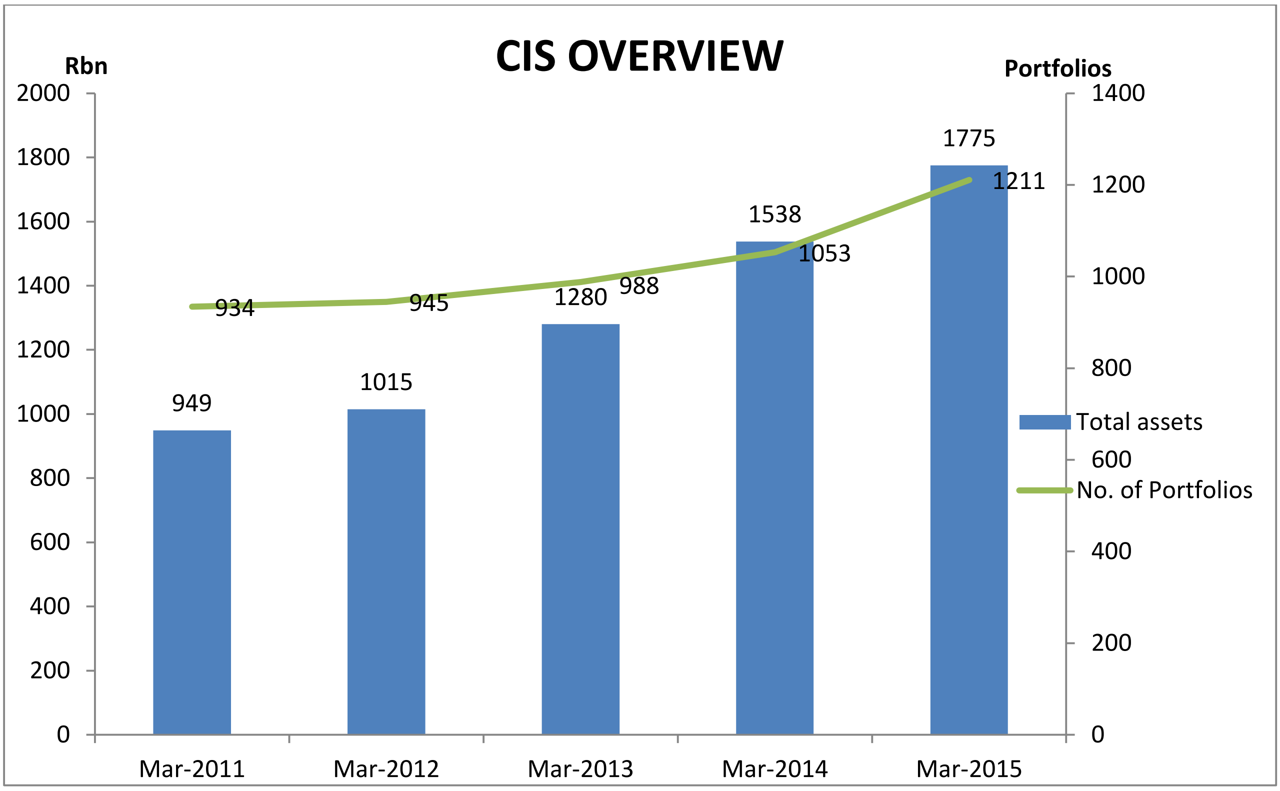
The total invested value was R661 billion five years ago. The R177 billion net inflows in 2013 represented an increase of 47.5% on the 2012 net inflows. As a means of diversification, the industry offered investors a wide variety of portfolios, numbering 1 062 in 2013. Statistics provided by ASISA clearly show the rise and growth of this industry.

Despite the seemingly relative economic significance of the mutual funds industry, only a few scholars have studied this industry. To the best knowledge of the researcher, no previous studies have investigated style investing. Du Toit (2012) reported significant value effects from all segments of the JSE main board. Another study conducted by Hsieh et al. (2012a) showed that four out of the six managers investigated underperformed their respective passively-replicated style benchmark. These studies provide a solid foundation for other scholars as there is quite a big gap in the literature from the South African perspective. Accordingly, this study aims to contribute to the small but growing literature on style investing from the South African perspective.

1.2 Background of the study

The unit trust investment vehicle has been significant in well-developed capital markets since the 1990s (Njeri, 2012). As one of the world's most developed capital markets, South African CIS are growing aggressively. The figure below, drawn using values sourced from ASISA (2015) shows how this industry grew from 2011 to 2015. It uses only Rand (R) dominated funds or portfolios.

Figure 1: CIS overview



Data sourced from www.asisa.org.za

The figure above reveals a surge in both total assets under management and the number of unit trust portfolios in South Africa.

Unit trusts can best be defined as private engagements that pool funds and resources from different types of savers to generate a large pool of funds which they then invest in different kind of assets like small caps, large caps, the money market, bonds and property with the aim of generating higher returns (Njeri, 2012). Unit trusts can therefore be seen as a vehicle to achieve wide diversification and higher returns for small investors who may only have small sums of money to invest (Thomas, 2012). Investments are made on behalf of contributors that can also be regarded as investors (Njeri, 2012). They are therefore not involved in day to day decisions about how and where their money is invested. The types of asset classes or products chosen by investors largely depend on their appetite for risk, financial goals, time frame, pre-investment diversification attempts and the availability of capital (Njeri, 2012).

Within the funds industry, portfolio managers and investors have come up with a simple way of dissecting assets and groups or classifying them according to their behaviour, relationship, performance and their ability to grow in the future. When portfolio managers and other financial experts create portfolios, they first decide what types of assets to invest in and what proportion of the money to put in a single asset incorporated in their funds (Barberis and Shleifer, 2003). In other words, they group all similar assets into broad groups and name these groups according to the types of constituents held in each group. These groups may range from value stocks, to growth stocks, small-cap stocks, mid-cap stocks, large-cap stocks, government bonds, real estate and venture capital. These asset classes are termed “styles” and the process of allocating funds across styles, rather than among individual securities, is known as style investing (Barberis and Shleifer, 2003). In this sense, investors who distribute their money across style levels rather than individual asset levels are called style investors. Style investing refers to “a manager’s adherence to some pre-defined specific asset allocation strategy” (Ahmed and Nanda, 2001: 1). The procedure of style investing can be used to identify the strategies and direction taken by each mutual fund. As suggested by Wahal and Yavuz (2013), this technique may hold very useful predictive powers, especially when it comes to predicting returns.

Given the large pool of stocks, portfolio managers have a choice of wide-ranging strategies. These managers can either be active or passive. Active managers strive to beat the market index through frequent buy and sell strategies while passive managers do not make any attempt to beat the market index; rather, they buy and hold stock for a prolonged period of time (Barberis and Shleifer, 2003, D’Arcangelis and Rotundo, 2014). In addition, some managers believe they have selectivity skills, i.e., they have the ability to spot stocks that will grow and generate profits. All these strategies have advantages and disadvantages that will be discussed further in the literature review.

The concept of behavioural finance also has much influence in style investing because managers are evaluated by comparing them to their peers. Peer comparison influences managers to introduce herding behaviour in the market in that they do what their peers do in order to revive their careers even if they do not believe in the strategies implemented by their peers (Gilmour and Smit, 2002). Pressure from external investors sometimes forces managers to change the initial mandate of investing in a specific style and drift to other winning styles in order to generate higher returns (Wermers, 2012). The phenomenon of drifting sometimes has negative results for investors because it kills diversification from an investor's point of view. It is detrimental if the drift goes to the style where investors also invested in a drive to diversify their investment. Since drifts are not disclosed, if they go to other styles of investment, investor diversification is deterred and investors are placed at a disadvantage if that style sustains a negative shock (Wermers, 2012).

Mutual funds have their roots in portfolio selection which was proposed by Markowitz (1952). Markowitz believed that the process of building a portfolio starts with observing the performance of a certain security and ends with making future predictions about that security. After observing and making predictions, the next stage is to choose the portfolio to place such security. In adding securities to a portfolio, the manager takes a broad look at changes in expected returns and discounted future returns against the variance of the portfolio which symbolises the total risk involved. Here, the rule of thumb is that managers must invest in stocks that have a maximum discounted value. However, the computation of the discounting factor is a problem since it cannot be done with certainty (Williams et al., 2012). Consequently, portfolio managers never score similar total returns at the end of the financial year.

Style investing has been praised for classifying comparable securities into a style, thus making it easy for the performance of the fund to be measured, by comparing it to the respective index (Barberis and Shleifer, 2003). The fact that portfolio managers invest funds on behalf of other investors introduces the element of the agency problem. It has been found that, in most cases, managers follow their mates or peers due to the fear that, in the end, investors will compare their manager's performance with their peer group. Chen and De Bondt (2004) found that, in extreme cases, managers would forgo their co-strategies and follow the dominant strategy in the market in order to remain competitive and appeal to investors.

The existence of external influence and the manager's own psychological considerations can best be described by behavioural finance. Ricciardi and Simon (2000) describe behavioural finance as a conviction that psychological considerations are an essential feature of security markets. This school of thought seeks to explain how emotions, human beliefs and investors' mental mistakes affect the decision-making process (Banerjee, 2011).

The concept of style investing was first proposed by Sharpe (1992). Since then, it has gained much popularity and many scholars have studied style investing from the perspective of different international markets. Evidence of style investing will be discussed in greater detail in chapter 2.

1.3 Aim of the study

This study aimed to establish the tendency of style drift in South African mutual funds and the long run relationship between South African indices. The relationship or lack thereof will further assist in the analysis of diversification possibilities through investing in funds that track different and non-co-integrated indices.

1.4 Concept statement and objectives

One of the key points in the investment literature is diversification; as investors would say, "do not keep all your eggs in a single basket". Unit trusts are often seen as the answer to this phenomenon as they have the ability to invest in many stocks with less starting capital requirements. The problem arises when investment is made through style investing, where one invests in many stocks with the same characteristics and almost the same performance in different prevailing economic cycles. Again, a solution to this manifestation is to invest in different investment styles which display largely different fundamentals and performance. The finance literature postulates that some styles are deemed the opposite of each other and are thus negatively correlated. A negative correlation between indices is believed to be the best case scenario since negative disturbance or shock in one style will not have spillover effects on the other (twin) since they are negatively correlated. However, this is very theoretical, and a fund's style is entirely up to fund manager's selection and philosophy.

The interdependence between styles and sectorial indices in South Africa has not received much attention. If some investments are repeated in many styles (which is the case in the South African stock market, where some shares in different sectorial indices also appear in small caps and the top 40), a negative shock to some stocks will obviously affect many styles and pose a threat to investors who strive to diversify their investment by investing in different indices. Following the growth of CIS, it is therefore important to establish how correlated styles and local indices are within the economy since they are used as a starting point and benchmark when assigning asset allocation weightings and modeling risk. Moreover, it is important to determine if fund managers actually follow promised/ advertised mandates conveyed by the name of the fund and select assets that truly belong to that particular style when allocating assets (investors' funds).

This research study sought to empirically determine the nature of possible diversification that can be obtained in the asset management industry by achieving the two following objectives:

- To analyse the long-run relationship between six different JSE indices (i.e., value, growth, small cap, large cap, industrials and resources); and

- To investigate and analyse the presence, causes and duration of style drift in the sampled funds that constitute the aforementioned six indices.

By establishing the patterns between changes in long- run relationships and style drift, the study addressed the following questions:

- What is the long-run relationship between investment styles and selected sectorial indices in the South African stock market?
- Can diversification be achieved by investing in different styles and funds replicating different indices in South Africa?
- Does style drift in South Africa follow any pattern?
- Do fund managers make attempts to control style drift?

1.5 Significance of the study

This study was motivated by information provided by ASISA which clearly illustrates that CIS in South Africa are growing at a faster rate than ever before. As noted earlier, it is important to determine the relationship between funds and indices of investments. This enables investors to select appropriate strategies to diversify their investment. Furthermore, this study sought to determine the relationship between a fund and its twin and other sectorial indices. The literature posits that a fund and its twin are negative reflections of each other in all aspects. However, this hypothesis remains untested in the South African market. Testing the long-run relationship in conjunction with style drift and stock picking provides better insight into the possible level of diversification and thus reduces risk.

1.6 Research methodology

In order to achieve the study's two objectives, two different models were used to provide solid, combined conclusions. The absence of long-run relationships are crucial for portfolio diversification. On the other hand, asset allocation is also important for portfolio diversification and superior performance. The study was consequently built on these two different complementary angles of portfolio diversification objectives. It is underpinned by the Engle-Granger two-step procedure to establish long-run relationships. This model was used in the form of a bivariate model to establish long-run relationships between six selected South African indices over a period of eight years. In line with Khan (2011), daily data was used to research long-run relationships between indices. Khan (2011) proposed that information flows instantly in financial markets. Therefore, it is necessary to use daily data because market participants, in turn, process information as it flows in.

Following the long-run relationship investigation, the study used Sharpe's (1992) asset class factor model to establish how managers allocate funds between stocks that constitute the six indices used in this study. Through returns, this model clearly shows which index each mutual fund follows in the selected sample. The results from both models thus provide all-inclusive views of long-run relationships between indices and how managers allocate funds in the presence of the discovered relationship. Data points and how data was collected will be further illustrated in Chapter 3.

1.7 Outline of the study

The remaining chapters of this study are structured as follows. Chapter 2 presents a literature review which is divided into the theoretical framework and empirical evidence. Chapter 3 discusses the research methodology employed for the study and the data sources. Chapter 4 presents and analyses the results and Chapter 5 provides conclusions and the recommendations arising from the findings.

1.8 Chapter summary

Chapter 1 provided the introduction and background of this study. The key words and concepts (i.e., style investing, style drift and mutual funds) that are relevant to this study were introduced. Having highlighted the problem and questions related to this study, the local and international literature in this field is reviewed in the following chapter.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

This study evaluated style investing and style drift from the perspective of the South African market. This chapter reviews the previous local and international literature in this field. The literature review provided the researcher with a clear picture of what factors to take into consideration as the study progressed further to conduct tests. This chapter examines the theoretical framework of style investing and mutual fund operations. Thereafter, the empirical evidence is reviewed and reported. The review is not confined to current models, but travels back in time to the roots of the models utilised in this study. This chapter further reviews the findings of previous studies and identifies areas of agreement and disagreement.

2.2 Theoretical framework

The performance of funds and investment strategies has been a focus area for financial experts and scholars for many years. The large number of investment strategies and constant innovation has led to an increasing number of financial products. One of the most acknowledged products are mutual funds' investments, which are referred to as unit trusts or CIS in South Africa. Mutual funds are much praised and utilized to achieve diversification. Moreover, these funds are managed by highly qualified professionals and investors are therefore promised quality service (Sarpong and Sibanda, 2014). Mutual funds can either be actively or passively managed. Active managers always strive to beat the market index through frequent buy and sell strategies while passively managed funds are dominated by buy and hold investment strategies. It is worth noting that mutual fund managers will always seek the best possible strategies to deliver superior returns, irrespective of whether they are active or passive managers.

2.2.1 Concept of style investing and mutual funds

The concept of style investing was proposed by Sharpe (1992). Sharpe (1966) and, later, Jensen (1968) focused on the performance of mutual funds in order to gauge the selectivity skills of managers and their results and conclusions are still relevant in current markets and are hardly challenged. Sharpe (1966) and Jensen (1968) compared mutual funds' performance against their respective market benchmark. They concluded that managers do not possess the necessary selectivity skills to produce superior returns and that returns based on selectivity skills do not persist (Brown and Harlow, 2002). Jensen (1968) founded the philosophy of asset pricing which emphasizes the grouping of assets according to their corresponding systematic risk levels.

Selectivity skills can play a major role in style investing, but investment style also has a significant, direct influence on how fund returns are derived, i.e., style itself, structure, market operations and constituents. Basu (1977) seminal study documented the benefits of grouping assets with the same firm-related attributes into a single portfolio (e.g., market capitalization and book-to-value). Since such grouping is a partial definition of style investment, returns on a single investment in a fund will be highly correlated to its index, and, if this is true, there will be high significant value of β (beta) between the asset and the index and greater weighing will be given to that investment in the portfolio. However, styles consist of dynamic investment strategies rather than the pure buy and hold method or relatively fixed portfolio weights (Brown and Goetzmann, 1997). These strategies may range from rebalancing, to selling and dividend pay-outs.

2.2.2 Strategic asset allocation and psychological considerations

A mutual fund is created by adding different assets with related behaviour to one portfolio. Hence, a mutual fund is assumed to have its roots in asset allocation as proposed by Markowitz (1952). Harry Markowitz introduced the Modern Portfolio Theory (MPT) in 1952. It is based on the notion that investors can create an optimal portfolio by holding diversified assets with different risks (Markowitz, 1952). In this efficient portfolio, the returns on a single asset are less important than how that asset's value moves against the overall portfolio value. What really matters is that each portfolio must deliver the highest expected return at the lowest risk possible (Ricciardi and Simon, 2000). However, an efficient portfolio is deemed partially unattainable in style investing since external investors have much influence on the stocks picked by portfolio managers (Pástor and Stambaugh, 2002).

Chan et al. (2002) state that managers may do what is deemed irrational simply because they do not want to deviate from the benchmark and thus, discard the possibility of an efficient portfolio. Chan et al. (2002) referred to this phenomenon as "bunching at the centre". The strength of the agency problem is further intensified by the fact that the manager's performance is evaluated in comparison to the performance and strategies of his / her peers. Such scrutiny from outside investors is more likely to bring about herding in the market.

In the portfolio management and trading environment, financial experts are believed to trade or make decisions based on two strategies, momentum and contrarian strategies. Momentum investors tend to follow previous positive trends in the hope that such trends will persist in the future; they believe that if they buy now, they will sell at even higher prices in the next trading term (Schwager, 2012). On the other hand, contrarian investors will move in the opposite direction from momentum investors in the hopes that their decisions are wrong and that they will make a profit when there is price reversal shortly after momentum investors realise they made a mistake (De Bondt and Thaler, 1987). Momentum strategies attract a vast number of uninformed and irrational investors who join this flow to make profits. This is best known as herd behaviour. In terms of the contrarian strategy, the investor buys when the herd is selling and sells when the herd is buying (Sarpong and Sibanda, 2014). Herd behaviour is best understood by studying the concept of behavioural finance.

Ricciardi and Simon (2000) describe behavioural finance as the notion that psychological considerations are an essential feature of security markets. This school of thought seeks to explain how investors' emotions, beliefs and mental mistakes affect the decision-making process. It strives to provide evidence that mispricing of stocks and deviations from efficient market hypotheses (EMH) stem from the fact that markets suffer the most from human physiological considerations and external influence. Ross et al. (2008) describe EMH as a condition where market and share prices are fairly priced in which no arbitrage opportunities exist.

One of the basic assumptions made in economics and finance is that the markets are efficient and investors are rational at all times (Yalçın, 2010). Consequently, behavioural finance scholars have devoted much time and effort to producing substantial empirical evidence that markets are not efficient and investors have many biases that result in non-optimal decisions. It is further argued that even if mispricing can be identified in the market, exploiting it and driving prices to their intrinsic value can be very difficult (Williams et al., 2012). Bodie et al. (2010) maintain that this is solid proof that refutes the efficient market hypothesis. If market anomalies exist, prices and asset allocation cannot follow the trends predicted by EMH. Behavioural finance is a broad field that explores how market decisions are made. For the purpose of this study, only a few behavioural forces are reviewed.

Many financial experts have studied different economies across the world to identify possible herd trading which is largely driven by behavioural finance biases. Demirer and Kutan (2006) analysed China's stock market, the Shanghai composite and found no evidence of herd trading in this market. In contrast, Tan et al. (2008) found that the Shanghai market suffered from herd trading. With regard to the South African market, Sarpong and Sibanda (2014) produced evidence of contrarian investors scoring superior returns, which correspondingly means that there is herd trading in this market since contrarian investors benefit from the mistakes made by herd investors.

According to Swenson (2000), institutional investors ought to abide by static asset allocation. However, style allocations tend to vary with the style performance cycle. Fama and French (1992a) assert that efficient market theorists believe that the style cycle must at all times mirror changes in style risk and fundamentals. However, La Porta et al. (1997) and Lakonishok et al. (1994) suggest that that these style cycles can, to a large extent, advance due to irrational factors unrelated to risk or fundamentals as per behavioural finance theories. La Porta et al. (1997) and Lakonishok et al. (1994) developed the Local Stochastic Volatility (LSV) models which maintain that growth stocks are, in most cases, overvalued by naïve investors who put more emphasis on the past growth rate when estimating future returns, leading to higher bid prices.

While the LSV measure demonstrates the misevaluation of growth stocks, Barberis and Shleifer (2003) developed the B-S behavioural model to explain the style performance cycle. The B-S model mainly seeks to explain superior returns on value stocks. It further supports the notion that such superior returns are the direct result of contrarian investors or traders who recognise and exploit misevaluation and mispricing between growth and value stocks. Simply put, the B-S model includes style value traders and contrarians whose asset allocations are inversely related to the most recent performance (Teo and Woo, 2004).

2.2.3 Risk and return factors in style investing

Scher and Muller (2005) describe style investing as a growing and significant investment vehicle that is both a source of returns and a risk factor. Style is regarded as a source of returns since many managers and investors seek strategies that will enhance alpha, which represents the intercept in the regression model. Pástor and Stambaugh (2002) explain alpha as the figure that shows managers' skill in selecting the mispriced stock that is ultimately included in their portfolios. Style investing is regarded as one way to invalidate this argument. In cases where investors opt to invest in value stocks during a period when value style outperforms other styles, the value of alpha will be enhanced for every investment in value stock (Pástor and Stambaugh, 2002, Scher and Muller, 2005, Li et al., 2014). On the other hand, style is also viewed as a risk factor. It is suggested that asset pricing and performance measurement based on absolute returns are no longer efficient. Hence, the risk introduced by active conduct in the quest for returns cannot be ignored (Scher and Muller, 2005, Wahal and Yavuz, 2013).

The Capital Asset Pricing Model (CAPM) introduced the concept of returns on single or combined assets as compensation for the market risk borne by investors. Simply put, the CAPM asserts that investors need to be compensated by factoring the risk and time value of money (Pástor and Stambaugh, 2002). In addition, the CAPM proposes that these returns must exceed the risk-free rate and must be directly proportional to the investment sensitivity to market risk displayed by beta (β). More recently, it has been found that style investing alone can enhance returns, while unique style characteristics, operations and cyclical behaviour can introduce additional risk that cannot be factored into market risk with certainty (Scher and Muller, 2005, Li et al., 2014). Fama and French (1992b) demonstrated that variations in returns may be the direct result of style factors. Thus, it is crucial to acknowledge style as a source of risk. It is for these reasons that measurement models of investment performance started to incorporate style as a risk factor in order to better measure and explain performance. Fama and French (1993) and Carhart (1997) are amongst the scholars who documented these findings. It is, therefore, held that performance persistence studies that do not adjust for style risk or even market risk can result in incorrect estimation of performance persistence (Kahn and Rudd, 1995, Wermers, 2003, Barras et al., 2010).

2.3 Prior literature and empirical evidence

2.3.1 Styles investing explained

Portfolio managers classify assets into different groups such as value and growth stock, large-cap, mid-cap, small-cap and government bonds, etc. After categorising assets into classes, they then allocate funds across all the classes identified (Bernstein and organizacija kompozitora Jugoslavije, 1995, Chen et al., 2013). Barberis and Shleifer (2003) show that assets or stocks compressed in the same style behave in the same way and thus share common characteristics that can be attributed to fundamentals, markets and law. They further stipulate that some classes are temporary, while others are permanent. Temporary styles are experienced during unusual conditions or popular conditions in the business cycle. A practical example of a temporary style is a style that may eventually emerge during a bubble and may suddenly disappear after the bubble bursts. In addition, new investment styles may be created due to recent innovation in the financial markets (Barberis and Shleifer, 2003).

The bottom line is that style is made up of stocks that possess same similarities regardless of the state of the economy (Barberis and Shleifer, 2003). Due to this constraint, it is expected that assets in the same style will be correlated and produce nearly the same relative cash flows and returns. Thus, if the style is made up of technology stocks and this sector faces a negative economic shock, it is unrealistic to expect that some technology stocks will produce positive returns while others will produce negative returns, as they are in the same style and industry or sector.

2.3.2 Birth and demise of styles

Herd behaviour during an economic bubble may give birth to a new style which could disappear after the burst (Cooper et al., 2005, Maor, 2014). Moreover, a style may be created after good news is received about a certain particular stock. A typical example is the birth of the small stock style which was discovered directly after the documentation of the small-firm effect (Barberis and Shleifer, 2003). Likewise, bad news may lead to the death of a style.

When good news about a certain style hits the market, many investors will opt to invest in that style; this drives stock prices to higher levels until the style reaches maturity. Investors will be thrilled to be part of this price hike, and the style will face a dead end after all the fruits have been harvested and will ultimately disappear. Furthermore, the style may reach a dead end due to poor performance and when arbitragers move prices back to their true intrinsic value. However, this only happens if there was mispricing of constituents in the first place which, to a certain extent, is more likely to be present in glamour stocks (Barberis and Shleifer, 2003).

When a style performs poorly, there is always the alternative of changing its name, which signifies a move away from a style with a low premium towards one with a corresponding higher current premium (Cooper et al., 2005). Cooper et al.'s (2005) study analysed the significance of changing names on cash flow and overall returns. Their findings revealed significant changes in cash flows just after the name change even if fund managers did not tilt constituents to be in line with the new style reflected by the new name. This finding does not justify the suggestion that some investors' decisions are mainly affected by herding and irrationality rather than the fundamentals. The fact that Cooper et al. (2005) found a significant increase in cash flows without managers investing in constituents that are reflected by the new name suggests that investors channel funds without a thorough fundamental analysis.

There are two types of name changes, namely, cosmetic and non-cosmetic (Cooper et al., 2005). Cosmetic refers to a name change that is followed by a new investment style and changes in fund constituents. Non-cosmetic is when the change in the fund name is not followed by changes in investment style and no changes in funds' holdings or constituents (Cooper et al., 2005). It can thus be concluded that non-cosmetic name change is mainly supported by irrational investors who are affected by financial biases which can be better understood by studying the concept of 'behavioural finance'.

A practical example of a non-cosmetic name change is provided by Ahmed and Nanda (2001) and Wine and Sullivan (2001) who noted that after the burst of the technology bubble, managers changed the fund's name to mirror a move away from technology stocks to value stock even though the fund's constituents were never changed. During this period, name changes were very common. Fund managers will always change the name to imitate current business sentiment which may range from "small-cap", to "mid-cap", "large-cap", "value sock", "growth stocks", "technology", "resources", or "industrials". Cooper et al. (2005) add that name changes mostly take the form of switching from a "cold style", which is a style that experiences hardship in cash flows to a "hot style", which is a style that recently produced positive returns.

2.3.3 Shift in style and factors influencing style drift

Cooper et al. (2005) produced strong evidence that mutual funds are likely to go as far as altering their names to benefit from the prevailing hot style. This is usually harmless to investors who channel funds to portfolio managers with the aim of achieving growth and higher returns on their initial investment amounts. Typical examples of such investors are individuals who make early investments in their pension funds. Wermers (2010) maintains that fund shareholders and pension sponsors base their investment decisions on the information advertised and provided in the name of the fund. Non-cosmetic name change is, therefore, a threat to investors who are financially literate, who channel funds to managers with the aim of investing in their favourite stock only to find that managers did otherwise (Cooper et al., 2005).

Chan et al. (2002) assert that cosmetic name change is the best option. They note that fund managers must be transparent and replicate the constituents reflected in the name of the fund because these constituents must paint a picture of investment strategies at a given date. Therefore, the features or portfolio holdings must reflect an up-to-date investment style at all times.

The agency problem is among the many factors that contribute to a shift in style. Due to the fact that poorly-performing funds risk losing investors, managers are left with no choice but to try something different in order to revive their careers (Barberis and Shleifer, 2003). Thus, they will not hesitate to withdraw funds from cold styles which are deemed to be delivering lower returns and start investing in hot styles. When managers withdraw funds from cold styles to invest in hot styles, they withdraw them from a twin fund which is explained as the opposite of the fund to which the money is channelled (Barberis and Shleifer, 2003). Many investment strategies come in pairs. According to Barberis and Shleifer (2003), securities that share the same positive qualities create one style while those that share the same negative qualities make up a twin. In other words, a single style and its corresponding twin are the opposite of each other. Having said this, cash flows and returns on a single style are the direct opposite of cash flows and returns on the corresponding twin style. In this sense, when the growth style is over performing, the value style is expected to underperform since they are deemed opposites. This reasoning adds to the literature that seeks to explain why they are many name changes in the funds market. When there is a boom in a particular style, there is a corresponding burst or drought in a twin style where managers may, sooner or later, opt to changing the name rather than letting it fade away.

Cooper et al. (2005) maintain that name changes that are not accompanied by changes in fund holding generate higher cash flows, especially if the name reflects the hot style and if managers spend more on marketing the new name. Furthermore, Cooper et al. (2005) state that there is no relationship between cash flows and returns such that an increase in cash flows does not lead to improvements in performance. Thus, managers may eventually opt to hold many different, diversified stocks at one time to try to compensate for poor fund performance. Consequently, they participate in “style drift”.

Style drift is described as the propensity on the part of fund managers to change from one style to another (Wermers, 2010). Wermers’s (2010) study displays that style drift has been discovered in South Africa and at the global level. The tendency to drift is so strong that even self-declared styles tend to stray from their name and promised mandate. The literature reveals that labour incentives may play a major role in allowing managers to deviate from their given mandate. Style drift may also arise due to the fact that the characteristics of stocks change constantly. A typical example is when a manager invests in a small-cap style, and, as time goes by, this may substantially change to mid-cap due to investments from outside investors. In this scenario, there will be style drift even when a manager passively holds the same stock over time. This is confirmed by Khorana (1996) who used statistical measures R squared and tracking error (TE) to check which asset classes diverged the most from their mandates. The study found that large-cap funds tend to have higher investment or style consistency than small-cap and mid-cap funds. In addition, large cap funds were found to have lower expense ratios on average because of their style consistency.

It has been argued that, in most cases, style drift tends to positively affect the performance of a portfolio manager. Wermers (2010) postulated that managers are sometimes better off holding a vast number of shares or styles. This argument builds on the dimensions of profitability derived from economies of scale which is referred to as “economies of style”. The study also found that managers find themselves in a fruitful position if they broaden their investment spectrum. This suggests that managers might be better off if they reduce their investment in some styles and invest in other previously ignored styles.

Furthermore, Wermers (2010) argues that some managers possess a measure of neutrality that causes them to make an effort to identify mispriced stocks and take advantage of them irrespective of their style. Such managers are ready to take up any opportunity that prevails in the market at the time rather than restricting themselves to a certain style. Drifting from one style to another is more likely when opportunities exist in the area of a manager’s expertise. Another motivation for style drift is that styles deliver different returns over time (Wermers, 2010). What was accepted as the best strategy or style a year ago may be completely ineffective in the current and following years.

Chen and De Bondt (2004) paper on "Style momentum within the S & P - 500 index" provides concrete evidence that growth stocks outperformed value stocks during the period 1998 to 1999. However, this did not last long, as today's value style is deemed a winning style. This demonstrates that no style or mix of instruments will ever be a winning strategy in all market conditions or business cycles. Hence, managers always need to be ready to try to take advantage of prevailing market conditions and adjust their holdings when necessary.

Over the years, it has become the norm for expert portfolio managers and beginners to chase whatever style delivered good returns in the recent past (Pástor and Stambaugh, 2002). This stems from the agency problem explained in the section on behavioural finance. Since fund managers compete for fund flows and, hence, investors, they diverge from their beliefs to meet the needs of investors and, therefore, adjust their investment strategies (Chen and De Bondt, 2004). It is for this reason that Wermers (2010) found that most managers put less effort into controlling for style drift as long as they deliver good returns to their investors. Consequently, these managers are not inclined to revert to the desired style. Moreover, the literature documents that consistently reverting to the desired style does not necessarily provide higher returns (Wermers, 2012).

Teo and Woo (2001) suggest that there is a connection between performance persistence and investment style in the sense that future returns may mimic past returns. After testing this hypothesis, they concluded that past winners and losers mimic their previous performance. These findings support style drift if a fund delivered poor previous performance. Even though Teo and Woo (2001) support managers who execute style timing, the real relationship between style consistency and fund performance is unclear.

Style drifting is mainly associated with active trading (Wermers, 2010). Managers that practise frequent, active trading find themselves managing drifting portfolios. However, active trading itself poses the problem of increasing correlation between previously un-correlated stocks which can introduce unforeseen risk. Wermers (2010) notes that investors who practise active trading, be it as a result of overconfidence or expertise, have a good history in portfolio management since they often produce higher returns. Chen and De Bondt (2004) add that approaches which rely on buying stocks that are in current favour (past winners) and selling those that are deemed to be out of favour (past losers) provide positive returns for a time interval of a year and more. These managers are said to achieve higher performance levels than their non-drifting colleagues. In contrast, Brown and Harlow (2002) found that style consistent managers deliver higher returns than active managers who drift frequently.

Susceptibility to style drift has its roots in both passive and active components. While there is no final consensus on this issue it seems that managers, both active and passive, are sometimes forced to engage in active trading to compensate for style drift and possibly rebalance the portfolio (Wermers, 2010). Changing from style to style comes with administration costs which must be taken into consideration before the drift. Managers of small funds are said to practise more style drifting when their funds grow to higher levels and they deliver higher positive returns after drifting even after accounting for both trading and administration costs (Wermers, 2010).

Prior to Wermers (2010) study, Brown and Harlow (2002) found that funds that stick to their mandate perform better than funds which practise style drift. These contradictory results show that markets are susceptible to change within a short period of time. Using the USA data set provided by Morningstar for the period 1991 to 2000, Brown and Harlow (2002) also concluded that consistent managers produced higher relative and absolute performance than their colleagues who relied on style drift. There are three possible reasons for this.

Firstly, it is expected that funds that resist drift will display a low portfolio turnover which will correspondingly result in lower transaction costs than funds that entertain style drift. Moreover, Brown and Harlow (2002) demonstrated that reducing turnover and controlling for fund expenses are of vital importance if a fund manager is motivated to deliver superior performance. Higher portfolio turnover results in higher expenses. With higher investment fees, funds that pursue style drift and incur higher turnover rates are more likely to be replaced or lose investors (Brown and Harlow, 2002).

Secondly, fund managers that strive to stick to one mandate experience fewer asset allocation errors. Managers that specialize in a single mandate develop more skills in selecting securities than those that always try to time their portfolio decisions (Brown and Harlow, 2002).

Thirdly, given that investors will always want to evaluate managers' decisions and performance, style consistency is an important tool to combat this agency problem since it always provides a correct rating index. Evaluation is difficult when a manager has invested in many stocks that belong to different indices. Hence, maintaining style can demonstrate managers' abilities to potential investors (Brown and Harlow, 2002).

While Brown and Harlow (2002) and Bubna et al. (2013) reported no benefits of style drift, Wermars (2010) reported higher returns for managers who execute style drift. However, Verbeek and Wang (2013) mitigated the discrepancies by stating that style drifting and stock picking became successful after the Securities and Exchange Commission (SEC) imposed quarterly disclosure requirements on all mutual funds in 2004. This consolidates these two contradictory findings, especially because Brown's study was conducted in 2002, while Wermer's was in 2010.

2.3.4 Performance and stock selection

Style consistency does not necessarily mean a buy and hold investment strategy, but refers to the tendency to consistently invest in the same style.

Barberis and Shleifer (2003) suggest the reasons why style investing is prevalent among individual and institutional investors, especially in the recent past. Firstly, the construction of asset classes helps investors to examine the performance of mutual fund managers in comparison with other managers in the same style. This is because style creates a peer group of managers who employ similar strategies. Furthermore, the style states the investment objective and thus aids the investor's decision-making (Allen et al., 2010). Nowadays, portfolio managers are assessed relative to the performance of a certain benchmark which might be a style such as value stocks, growth stocks, large cap, small cap, resources or industrials. Secondly, grouping stocks or securities eradicates the situation where there are a vast number of stocks to choose from, and allows for information symmetry. Moreover, Barberis and Shleifer (2003) state that it is much better and easy to choose and invest in six styles than to choose from thousands of random-listed securities. For the aforementioned reasons, style investing has received much attention over the past decade, albeit with no consensus.

Barberis and Shleifer (2003) extend the spectrum of style investing by positing that there is a higher rate of correlation between assets that are compressed to constitute a single style. Immediately after assets are categorized to one style, they fluctuate more closely with that style after classification than before. Consequently, correlation intensifies between assets in the same style while it fades away amongst assets in different styles (Barberis and Shleifer, 2003). Therefore, assets that are grouped into a precise style should start to co-move with that style and other constituents in that style after they are added to the style.

Having reviewed style investing, it can be concluded that managers tend to be pushed by herding behaviour towards investing in past performing styles by simply withdrawing money from twin styles. This is done in order to accumulate higher returns since style investing yields common factors in the asset returns that are categorised under the same style. These higher returns are completely unrelated to cash flows as per Cooper et al. (2005). Further to this, Verbeek and Wang (2013) assert that even if mutual funds start investing in other styles, in the end, they are able to generate returns that are comparable to their target mutual funds after taking into account expenses and transactional costs.

The literature thus shows that style investing has the potential to create an efficient and conducive trading environment which is subject to less risk. However, this is only attainable if managers forgo beating the index and try by all means not to stray away but remain near it. In this case, the buy and hold strategy (passive trading) will meet the objective. From the CAPM and asset allocation theories postulated by Markowitz (1952), a passive investment strategy has always reduced the rate of risk that portfolio managers face. However, the presence of managers who engage in active trading, like drifting between funds and the rise of individual switchers, has introduced high risk in portfolio management (Barberis and Shleifer, 2003). Barberis and Shleifer (2003) identify two types of investors in style investing, i.e., "fundamental traders" and "switchers". Fundamental traders are those who consistently hold stocks and stick to their estimated target intrinsic value. On the other hand, switchers are those that always move to whatever style seems favourable at the time or even ahead which is regarded as active trading. Like any other investor, switchers allocate funds to a particular style and decide on allocation proportions. In addition, they put more weight on figures from the recent past when deciding on their allocation proportions (Barberis and Shleifer, 2003).

Revisiting the case of induced risk and correlation between previously un-correlated stocks noted above, one can visualize a scenario with two stocks, i.e., R and S. There is good news in the market about stock R, with the existence of switchers in the market. Stock R experiences an increase in cash flows through an increase in demand which progressively leads to its price deviating from its intrinsic value which is given by fundamentals. If there are any limitations in the supply of stock R, its price will keep rising over the price supported by fundamentals. Recalling that there is a style and a twin, the funds used to purchase stock R are withdrawn from stock S which is a twin of R. The withdrawal of funds from stock S will drive demand and prices down as predicted by the law of demand. A major threat identified by Barberis and Shleifer (2003) is that should this so-called good news be based on noise, switchers will cause huge destruction in the market.

They add that, if switchers realize their mistake, the interest in stock R will disappear and push prices even lower than they were before the noise. This can be compared to the bursting of a bubble. On the arrival of noise, this incident is inevitable and the presence of fundamental traders is not enough to stop it. Moreover, as switchers keep choosing stock that is in favour, they create correlation between two previously unrelated stocks, leading to calls for portfolio rebalancing to all managers (Barberis and Shleifer, 2003, Qiang and Shu-e, 2009). For these reasons, active trading is seen a root of induced risk in the field of portfolio management.

It make sense to critically analyse style investing in relation to or concurrent with behavioural finance. The fact that funds are monitored by managers who are human beings that are subject to market pressure and human error means that behavioural finance is relevant.

There will always be a dispute between investors and fund managers since managers invest funds that are not theirs. This introduces the agency problem since investors may want to consistently gauge a manager's performance. Given the theory of returns anomalies in financial markets, an investor may expect to see his/her manager follow certain approaches that have been proven to produce a higher return mean while the manager might feel that too much risk is involved in those strategies (Wine and Sullivan, 2001, Dybvig et al., 2010). Furthermore, Chan and Lakonishok (2004) postulate that because portfolio managers fear damaging their reputation and career, they may opt to follow approaches that will maintain their position near the market benchmark regardless of the rationality or irrationality of those approaches. This tendency is described in behavioural finance as obedience, the disposition to do inappropriate things or make wrong choices if taught to do so by a specialist, authority or represented figures (Ackert and Deaves, 2009).

Wine and Sullivan (2001) and Chan and Lakonishok (2004) add that managers are also examined on the level of their holdings in comparison with their peers' level of holdings. Chan and Lakonishok (2004) investigated the rivalry between value and growth stocks to explain why, of all the types of styles, managers may choose to invest in growth to revive their careers. They found that growth stocks are usually chosen because of their favourable history of good returns. Thus, they are a good weapon to combat the agency problem, enhance the manager's reputation and revive their career.

On the other hand, value stocks are neglected because they are regarded as stocks that have recent bad performance but with room for improvement and these stocks are regarded as posing a higher risk than growth stocks. In other words, value stocks may take some time to deliver good positive returns and they pose a threat if investors evaluate managers that employ a value strategy compared to managers who follow growth stocks at the prevailing time. Factors such as extrapolation bias, herding and behavioural traits remain the pillars for managers in choosing growth (value) over value (growth) (Chan et al., 2002). Extrapolation is the process of estimating value or facts beyond the original range on the basis of a relationship between estimated variables (Klaassen, 2013). Chan et al. (2002) note that the phenomenon of "bunching in the centre" may also discourage fund managers from following value investing since it is likely to deviate from the overall market index more often before it delivers positive returns.

Another reason for managers to effectively bunch in the centre is that they may employ strategies that cannot be easily presented to investors, like book to market analysis. As a result, they may opt to invest in well-known stocks that could ultimately create a portfolio that does not diverge from the benchmark (Chan et al., 2002). In addition, fund managers do not diverge from the strategies implemented by their peers (Banerjee, 2011). By default, value stocks become profitable over a wide range of time horizons while growth (glamour and past winners) stocks produce instant, positive returns as well as the added advantage of price momentum in the short-term.

2.3.5 Value, growth, and other investment strategies

With regard to value and growth as investment strategies, stocks are classified into two categories depending on their characteristics and performance. Value stocks are defined as those that have a relatively low market price in relation to some estimation of intrinsic value, such as price to book value (P/B), price to earnings (P/E), and price to cash flow (P/C) (Yen et al., 2004). It is widely accepted that value and growth style should be based on the ratio of book-to-market value (B/M) and small-cap, mid-cap-and large-cap should be distinguished based on a firm's market capitalization (Chan et al., 2002). These key criteria are said to be useful indicators of style. However, in a few cases, this theory might not hold. Chan and Lakonishok (2004) demonstrate a typical situation where such belief might not hold. They note that some stock would be deemed cheap stock by looking at its book to market ratio when other explanatory variables, like dividends and earnings relative to price, might make the stock less attractive at face value. They add that such disparity suggests that other measures might be useful in figuring out the investment strategies necessary for that stock, but not where they really belong.

In the literature on style investing, much attention has been paid to the competition between value stocks and growth stocks. Chan and Lakonishok (2004) are amongst the scholars that have analysed this competition. The value style is favoured for delivering superior returns over the growth style. This conclusion was drawn after taking into consideration the financial market experience of the late 1990s.

Chan and Lakonishok (2004) ranked portfolios according to their B/M; the highest ranked portfolio was value and the lowest was the glamour portfolio. In terms of returns, the value portfolio delivered monthly average returns of 1.83 per cent while the glamour portfolio produced a monthly average of 0.30 per cent despite the fact that the market betas were close to each other. They used these finding to discount the suggestion that systemic risk plays a role in determining a fund’s returns. Such findings can be directly linked to Fama and French (1992a) proposition on the “death of beta”.

Market anomalies cannot be discounted when discussing the performance of these two investment vehicles. Basu (1977) suggested that stocks with lower price/earnings (P/Es) usually deliver higher returns than stocks with higher P/Es. Chan et al. (1991) also found strong evidence that the value strategy delivers higher returns than the growth strategy. Their results were obtained from a detailed investigation of the Japanese market’s past returns. The findings were confirmed by Fama and French (1992a) who also found that the value strategy produced higher returns due to the increased level of risk, which is in line with the rule of thumb: higher risk, higher returns. Chan and Lakonishok (2004) noted that the academic community has largely agreed with the proposition that, on average, value strategies do better than growth strategies. Having said this, this community is cautioned not to forget Lakonishok et al. (1994) finding that cognitive biases drive investor behaviour and that the agency problem of portfolio managers discussed earlier was at the root of the so-called higher rewards on value investing. The counter argument to these findings is offered by Chan et al.

(1995) who dispute that such bias is strong enough to explain the discrepancy between value and growth strategy investing.

Some scholars have documented that the rewards of value investing exceed those of growth investing in the long term. These returns are believed to be both larger and more realistic as the investment threshold widens. Rousseau and Van Rensburg (2004) suggest that higher rewards compensate for investor patience since their investment period is mandatorily required to be long.. Using data from the JSE, Rousseau and Van Rensburg (2004) found evidence of low P/E stocks outperforming high P/E stocks after adjusting for risk. The study confirmed the presence of the “value” effect and concluded that value stocks yield higher returns than growth stocks.

Chee et al. (2013) define value in terms of the prospective yields implied by current prices and the investment’s expected future cash flows. However, purchasing cheap stocks and allowing them to gain substantial value over time is not the only aspect of a value investment approach (Rousseau and Van Rensburg, 2004). There is a paucity of in-depth studies on the well-known fundamental analysis axiom that this investment strategy is best understood as a long-run method of delivering higher returns. The reason for this discrepancy boils down to an investor’s psychological considerations and agency costs. The literature on managers’ psychological considerations proposes that investment managers tend to rely more on simple “heuristics” when they make investment decisions which create the possibility of judgment biases during the investment horizon (Chan and Lakonishok, 2004, Banerjee, 2011). More precisely, managers tend to extrapolate historical performance too far into the future (Ibbotson et al., 2013). This concept of biased extrapolation was confirmed by Chan et al. (2003) who documented evidence of biased extrapolation in the pricing of value and glamour stocks.

Rousseau and Van Rensburg (2004) shed light on this on-going debate about value and growth stocks from a South African perspective. Using data from the JSE, Rousseau and Van Rensburg (2004) analysed trends between low P/E stocks and high P/E stocks. The results of the study reveal that there is little difference in the returns of the two stocks in question from top to bottom P/E ranked from high, to low, for a period of six months. Noticeably, as the time or investment horizon widens, the value portfolios deliver superior returns. These results confirm the proposition that value investment is a more reliable source of higher returns in increased investment horizons. A significant change or turnover in returns’ distribution is witnessed at a time horizon of 18 months and more. At this time interval, low P/E stocks start to outperform high P/E stocks or portfolios. Moreover, the likelihood of low P/E stocks outperforming high P/E stocks and benchmarks is found to be significant and strong at the time horizon of eighteen months and beyond and comparatively insignificant as the market capitalization of the portfolio becomes larger (Rousseau and Van Rensburg, 2004).

More controversially, the study by Rousseau and Van Rensburg (2004) reports a higher standard deviation for smaller value portfolios held for much longer periods. This means that the level of risk increases for such portfolios. The same is true for short-term concentrated value strategies. This risk is partially associated with the fact that some stocks continue to change their characteristics over time, as proposed by Wermers (2010). Rousseau and Van Rensburg (2004) note that another reason is that such an event can be linked to the fact that the return distribution of these portfolios is skewed which successively leads to higher standard deviations being estimated, but this does not necessarily mean an increased possibility of downside performance (Rousseau and Van Rensburg, 2004).

Nonetheless, investing in value stocks and waiting for prolonged periods before the investment starts to pay off is deemed a winning strategy. Rousseau and Van Rensburg (2004) suggest that rather than simply buying cheap stock to create a value portfolio, one should create a portfolio using shares that ware the cheapest 12 months ago because there is a strong possibility that current, lower P/E shares may continue to exhibit poor performance. If this happens, one will be required to hold this portfolio for a more extended period which takes one back to the argument of the risk associated with holding a value portfolio for longer horizons.

Using New York Stock Exchange data, Lakonishok et al. (1994) also documented that value stocks outperformed glamour and growth stocks. They note that value stocks report higher returns for several years to buy and hold long-term investors. In contrast to Rousseau and Van Rensburg (2004), they sorted their data by B/M value. Value stocks outperformed growth stocks over a period of five years following portfolio inception. These superior returns were obtained after adjusting and controlling for size. Combining and consolidating the conclusions of these two studies, one can conclude that value stocks delivered superior returns after controlling for difference in size and adjusting for risk.

Passive buy and hold investors suffered the most during this abnormal state of the economy. They were unable to recover due to the limited life span of their assets and personal liquidity constraints. Simply put, these investors couldn't hold assets for longer horizons. As a result, they had to sell at even lower prices and, therefore, incurred losses. This led Faber (2009) to regard holding any asset during a global financial crisis as a "decidedly unwise course of action". Earlier, Chua et al. (1987) described the buy and hold strategy as one that offers 100% (per cent) accuracy in forecasting the bull market and 0% (per cent) accuracy in forecasting the bear market.

Bauman et al. (1998) analysis validates that smaller companies often produce higher returns than larger companies in and outside the USA. Since value firms are usually small, it can be argued that the value premium may be partially due to the "size effect". This is confirmed by Banz (1981), who documented a relationship between stock returns and the size of the company.

Dechow and Sloan (1997) suggest that the greatest opportunity to earn excess returns in the market is when one takes a contrary position against naïve investors who rely more on forecasts; they show that this is a special ingredient that is implemented by value strategies that, therefore, score more returns. Yen et al. (2004) conclude that value stocks have stronger predictive power for earnings in subsequent years, especially during the first two years after portfolio inception. Their findings appear to be in line with Fama and French's (2000) findings that showed that earnings and growth rates do not a follow random walk.

Some investors become excited about the past and current performance of a certain stock and quickly start adding it to their baskets, resulting in the overpricing of these stocks (De Bondt and Thaler, 1987, Brown et al., 2013). On the other hand, they overreact and abandon stocks that perform poorly and thus oversell them; when stocks fall out of favour, they eventually experience a severe drop in price. This offers contrarian investors an opportunity to go against naive investors and buy most of abandoned under-priced stocks which happen to be value stocks, while selling overpriced stocks, thus successfully outperforming the market (De Bondt and Thaler, 1987, Brown et al., 2013, Sarpong and Sibanda, 2014).

Aimed at demonstrating that a strategy that incorporates growth characteristics in value can provide superior returns in different investment horizons and business cycles, Ahmed and Nanda (2001) study shows that it is sometimes not a good idea to treat growth stocks and value stocks as mutually exclusive. Ahmed and Nanda (2001) proposed that growth and value can complement each other and produce superior performance.

Ahmed and Nanda (2001) argument stems from the fact that indices and mutual funds are created using univariate definitions such as B/P and E/P to differentiate growth and value. Univariate measures will always treat growth and value as mutually exclusive. Michaud (1998) and Brown and Mott (1997) posited that significant measures and superior performance can be achieved by incorporating other measurements or dimensions when assembling portfolios or style indices. While the notion of incorporating growth characteristics in value was not invented by Ahmed and Nanda (2001), it had never been tested and thoroughly evaluated. Using data from 1982 to 1997, it was found that incorporating growth characteristics in value produces more positive returns than those achieved using pure value strategies which are currently deemed to be winning strategies (Ahmed and Nanda, 2001).

Ahmed and Nanda (2001) study also analysed turnover ratio on style portfolios to come up with a concrete way of selecting stocks worthy of inclusion in a superior portfolio. They found strong evidence that stocks that lie at the centre between value stocks and growth stocks tend to produce superior returns. They produce better returns than value and growth stocks returns over two years of inclusion in a portfolio. However, this strategy calls for portfolio rebalancing every year. They add that "*the consistency of this strategy over different investment horizons and at different time periods shows that all value stocks may not be equal; some are more equal than others*" (Ahmed and Nanda, 2001: 3). Cremers and Petajisto (2009) added the importance of selection timing if portfolio managers really want to beat the benchmark. They propose a different way all together of creating a superior portfolio that can beat the respective market benchmark. They assert that fund managers can beat their market benchmark by taking positions that are different from the benchmark.

This section described and explained the common styles available in stocks and capital markets. The most common styles are value, growth, contrarian and momentum. Furthermore, some styles are purely based on a sector or segment like industrials, resources, cash and bonds which are distinguished on the basis of time horizon or maturity. On the other hand, some asset allocation strategies are based on market capitalisation like large cap, mid cap and small cap. The following section highlights empirical findings from the South African market perspective.

2.3.6 Some literature relevant South African market and empirical findings

With regard to South African evidence, Hsieh et al. (2012a) confirm international findings that equity funds' superior performance is mainly derived from replicating the style and making no attempt to beat the market index through stock picking. Hsieh et al. (2012a) note that these findings do not point to any significant variance between global equity funds and their corresponding style benchmark. However, using six well-established South African unit trusts, Hsieh et al. (2012a) found that four out of six managers underperformed their respective style benchmark. Moreover, they found that stock picking in South African funds destroys the value produced by replicating the style index or benchmark. These findings were documented after finding that selection return, which are returns in excess of those scored through replicating the investment style, are random and insignificant. They thus suggest that investors that wish to earn sound returns should passively follow or replicate a particular style. Furthermore, investors will be better off if they invest in exchange traded funds (ETFs) that passively replicate the mandate of style or market benchmark at minimal cost (Hsieh et al., 2012a).

Active fund managers are praised for exploiting market anomalies and generate superior returns. Consequently, they are deemed to possess necessary skills to select stocks that offer higher returns. However, the empirical literature does not support this position (Hsieh et al., 2012a). It is argued that stock picking strategies are ineffective and do not produce returns higher than those achieved through replicating the mandate of investment style and market benchmark. Sharpe (1992) found evidence that superior returns to mutual funds are due to asset allocation rather than stock picking decisions made by fund managers.

Collinet and Firer (2003) analysed performance persistence between South African funds for the period from 1980 to 1999 and concluded that these funds' past performance tends to indicate performance for the following six months. More specifically, if an investor can invest in top performing funds for six months and continue rebalancing for the next six months, he/she would gain returns that are higher than the average returns of all unit trusts after discounting for transaction costs.

Yu (2008) used three South African indices to analyse the returns of unit trusts, namely the JSE Financial Index, the JSE Resource Index and the JSE Industrial Index. In addition to these local sector indices, three other style proxies were incorporated: large cap proxy, value proxy and the momentum proxy. The study covered the period 2001 to 2006. Yu's findings revealed that there is a strong significant relationship between South African unit trusts and that these investment vehicles leave insignificant residuals. Therefore, Yu's study also serves to confirm the insignificance of selection returns. Thus, stock picking strategies executed by active managers do not contribute to their integral investment style returns.

It is widely accepted in the literature that consumers or investors select investment funds based on performance (Bailey et al., 2011, Guercio and Reuter, 2014). They focus on recent performance and neglect the recent past. It is for this reason that Meyer (1998) asserts that it is important for fund managers to maintain momentum and good track records if they want to hold on to their existing investors and attract new investors. Investors flock in the direction where the most superior performance is identified.

It is still unclear which style dominates the other, since the literature documents different findings. Some researchers like Bernstein and Jugoslavije (1995) propose that the world may witness a reversal in certain investment climates. In search of a superior strategy, Siegel (2003) and Scher and Muller (2005) posit that a single style can have a favourable season. Furthermore, they stipulate that these periods of style dominance may be short-lived or may last for longer investment horizons. This is in line with Campbell et al. (2010) finding that performance between styles mostly depends on the nature of stock price movements.

Scher and Muller (2005) highlighted that, style rotation may sometimes not have a significant effect or even be noticed due to the fact that unit trusts keep changing their mandate and constituents, especially after rebalancing. This argument stems from the fact that it was found that funds with style mandate did not always strictly conform to this mandate (Scher and Muller, 2005). However, these findings contrast with those of Lucas et al. (2002), who found significant and robust excess returns on funds that implement rotation strategies. Bird and Casavecchia (2011) also found that rotation strategies deliver superior performance provided certain conditions are met. They note that rotation strategies will not deliver superior performance if value and growth portfolios are enhanced using market sentiment and financial health indicators (Bird and Casavecchia, 2011). However, the study acknowledges that such contrast may be a result of studies being undertaken in different market and different economic condition given a wide time frame at which these studies were conducted.

Since fund managers do not always conform to the funds mandate, therefore the possibility of style drift is high. It is therefore of utmost importance, that the relationship between indices are examine. This provides a clear picture of how diversification levels are maintained. Certain pairs of financial data are expected to be co-integrated or share a similar trend in the long-run. This long-run relationship may be a direct result of the nature of the data used or it can be influenced by market operations (Alexander, 1999). In the short-run, there may be deviations, which result in neither a similar trend nor a relationship. However, in the long-run, these variables may share a similar trend and relationship because of market forces, investor tastes and preferences which will restore long-run equilibrium (Ghosh et al., 1999).

2.3.7 Co-integration and Correlation relevance

Co-integration indicates the presence of common properties between the investigated variables. This common property limits independent variation between variables and forces them to share similar behaviour and trends (Khan, 2011). Effective risk management requires a thorough understanding of the nature of the data series in question (Alexander, 1999). For efficient management, volatility, fundamentals, correlations and other related financial attributes need to be known with certainty. Knowing the long-run, short-run stochastic trends in equity markets is crucial for portfolio managers, policy makers, and investors for pricing their assets and for diversification reasons (Kasibhatla et al., 2006). This renders co-integration analysis important for both short-run and long-run strategies. Portfolio managers are, therefore, expected to assign or determine their weights based on the results provided by co-integration or correlation models. Co-integration of variables has direct implications for diversification opportunities between the variables in question (Khan, 2011).

Many methodologies can be used to analyse short-run and long-run relationships. However, a significant proportion of these models appear to be inefficient and flawed. Kasibhatla et al. (2006) contend that many traditional money managers tend to rely on correlation analyses which are performed after differencing the original data series. Kasibhatla et al. (2006) strongly criticize this methodology, arguing that time series data lose important long-run information after being differenced, thereby rendering the results obtained in correlation methods inaccurate and misleading. Granger and Hallman (1991) also criticized the methodology of working with returns or differenced data. They showed that asset returns have “short memory processes”. Therefore, investment decisions made after consulting short-run asset returns are inefficient because the asset prices in the long-run are totally ignored when they most needed. Furthermore, correlation methodology requires more frequent asset rebalancing, whereas co-integration methods do not require rebalancing.

Alexander (1999) suggests that correlations are not adequate for risk management because they fail to account for lead-lag relationships like price discovery between spots and futures. Alexander (1999) also showed that index replication and portfolio optimization using the co-integration method may simply result in higher returns than the correlation method. Duan and Pliska (1998) developed a new method for testing short-run and long-run relationships in the securities market. In explaining their methodology, they postulate that, while correlation is the best in short-term investment decisions, co-integration methods are accurate in the long-term. The study concluded that these two methods are complementary and can, therefore, be used together to fill loopholes in the time series analysis. This is supported by Fadhlaoui et al. (2009) who found that establishing long-run relationships is not sufficient. For better insight on diversification opportunities, correlations must be known. If correlation coefficients are higher, the gains from diversifying between variables are minimal. On the other hand, if correlation coefficients are low, gains can still be acquired from diversification (Fadhlaoui et al., 2009).

Various scholars have found the co-integration methodology to be efficient. Taylor and Tonks (1989) suggest that the existence of co-integration infers the desecration of market efficiency. In contrast, Fraser and Oyefeso (2005) hypothesize that co-integration does not necessarily denote market inefficiency. They believe that if fundamentals in different markets are co-integrated, there is a high possibility that their prices are also co-integrated. Alexander's co-integration does not necessarily mean co-movements in returns but simply denotes co-movements in asset prices.

The literature on co-integration reveals interesting but contradictory results. Corhay et al. (1995) conducted a study on five major Pacific-Basin markets and confirmed only one co-integrating vector. Interestingly, Pan et al. (1999) conducted the very same study four years later and reported no co-integration vector between five Pacific-Basin markets.

Dickinson (2000) found that there was co-integration between European stock markets after the 1987 stock market crash but no co-integration vector prior to 1987. In contrast, Chan et al. (1997) found no evidence of co-integration between several European stock markets, including those that Dickinson studied, especially after the 1987 stock market crash. Furthermore, Alexendre and Thillianathan (1995) discovered long-run relationships between Asian-Pacific equity markets, but only after the indices were represented in local currency and not in common currency. Alexander (2001) thus concluded that co-integration equity markets should be analysed using local currency indices. It is, therefore, necessary to continue searching and confirm the existence of the co-integrating vector on a regular basis to avoid reliance on flawed and out-dated reports.

Khan (2011) notes that it is important to consider the nature of the original data when searching for co-integration. Furthermore, Khan (2011) believes that it is more acceptable to use daily data rather than monthly data when searching for co-integration between stock markets. This is because information flows instantly and market participants react very quickly to market price information. It is, therefore, important to be aware of the nature of the variables and how often they are processed in the market before deciding on data frequency.

2.4 Chapter summary

This chapter provided the foundation for this study. The literature reveals that there is no consensus on the concept of choosing the investment index. Furthermore, there is no consensus on which style delivers superior returns. It is for this reason that Wermers (2012) suggests that a possible reason for style drift is that funds do not deliver consistent returns over time. A number of scholars, like Hsieh et al. (2012b); Ibbotson et al. (2013) and Brown et al. (2013) found that investors base their investment decision on the latest returns. However, this tends to contradict the fundamentals of growth stocks since they are defined as stocks that stand a better chance of growing in a short period of time. Cronqvist et al. (2013) dispute that returns are used as the selection criterion. They maintain that investment decisions are genetic in the sense that people have an innate preference for existing and available indices.

The literature review provided direction for this study in setting up models that are able to deliver efficient and interpretable results. With local scholars having focused on studying performance resilience and herding behaviour in the South African market, this study takes the unique position of combining long-run relationships and asset allocation with intentions to evaluate levels of diversification, thereby leading to the risk faced by investors.

The following chapter outlines and explains the research methods employed in this study.

CHAPTER 3: DATA AND METHODOLOGY

3.1 Introduction

This chapter describes the sources of data as well as type of data used to achieve each of the study's objectives. The literature review identified appropriate methods for modelling different kinds of data. These were used to model different kinds of data for the study's objectives. This chapter describes the kind and frequency of data used as well as data sources and data points.

3.2 Data

To achieve the objectives stated in Chapter 1, secondary data was collected, mainly from McGregor BFA and ProfileData. Data was collected for a period of eight years, from 2006 to 2014. The choice of this period was guided by the life span of the sampled unit trusts. Two different types of data frequency was collected for the two different objectives. Weekly data were collected for the first objective where the ultimate aim was to answer questions related to style drift; and daily data were used for the second objective which aimed to evaluate long-run relationships between selected JSE indices.

Table 1 below describes the data collected and the frequency used to evaluate both style drift and long-run relationships.

Table 1: Data description

OBJECTIVE	VARIABLE	SOURCE	PERIOD	DATA POINT	FREQUENCY
Number 1 (style drift)	Closing prices	McGregor BFA	427 weeks	Last day of the week trade (7 day week)	Weekly
Number 2 (long-run relationship)	Closing prices	McGregor BFA	2019 days	Daily closing price (5 day week). Other weeks will be short due to public holidays	Daily

Table 2: Terms, dates and observations (factor model data)

CYCLE	START DATE	END DATE	OBSERVATIONS
TERM 1	08-Sep-06	02-Nov-07	61
TERM 2	09-Nov-07	24-Dec-08	61
TERM 3	31-Dec-08	19-Feb-10	61
TERM 4	26-Feb-10	21-Apr-11	61
TERM 5	29-Apr-11	22-JUN-12	61
TERM 6	29-Jun-12	16-Aug-13	61
TERM 7	23-Aug-13	06-Oct-14	61
Total observations			427

Table 2 above provides a breakdown of how the data was separated in order to ensure that there were sufficient segregated periods or terms to use in the search for style drift. This is in line with Sharpe (1992), who asserted that the minimum efficient number of observations is 61 in order to obtain meaningful results from the asset class factor model which will be explained in the methodology section. Weekly observations were broken down into different terms, ensuring a minimum number of 61 observations per term. Terms were arranged in date ascending order. This strategy was implemented because this study evaluated style drift from the far past to the most recent past. Combining all the observations from the different terms, the number of observations amounted to 427 weekly observations.

To answer questions relating to style drift, and funds' behaviour and operations, four funds per index were selected. These were the top two and bottom two performers per style. A vast number of filters were applied to these data. Firstly, funds were selected based on the availability of data which had to match the study period. Secondly, the researcher avoided selecting funds provided by the same organisation to fill the number one and number two spots. Most importantly, data source-provided rankings were used as per the date the data was collected to identify the top and bottom achievers. This kind of ranking was provided by ProfileData and was obtained directly from this source. It is of the utmost importance to note that the rankings and fund performance change from time to time and, hence, a careful selection of the top and bottom achievers was crucial. The list of all unit trusts used is provided in appendix A.

Returns were computed using the following equation:

$$\text{returns} = \frac{\text{close}_1 - \text{close}_0}{\text{close}_0} \qquad \text{EQ 1}$$

To evaluate the question of the long-run relationships between South African indices, closing prices for the eight-year period in daily frequency were collected, as illustrated in Table 1 above. The study used six South African indices as follows:

1. FTSE/JSE LARGE CAP (J200);
2. FTSE/JSE SMALL CAP (J202);
3. FTSE/JSE RESOURCES (J210);
4. FTSE/JSE VALUE (J330);
5. FTSE/JSE GROWTH (J331); and
6. FTSE/JSE INDUSTRIALS (J520).

These indices were selected mainly because the paper seeks to discover if it's possible to diversify stock selection using them should they share a negative performance relationship. The same is true for selection of small cap and large caps. The selected indices were therefore the perfect place to search for short-run and long-run relationships and the possibility of diversifying using deemed negatively co-integrated and related pairs.

Table 3: Daily data cycles (segregated period strategy)

CYCLE	START DATE	END DATE	OBSERVATIONS
1ST 2 YEARS	08-Sep-06	05-Sep-08	500
2nd 2 YEARS	08-Sep-08	07-Sep-10	500
3rd 2 YEARS	08-Sep-10	07-Sep-12	502
4th 2 YEARS	10-Sep-12	06-Oct-14	517
8 YEAR PERIOD	08-Aug-06	06-Oct-14	2019

All data for the six indices were obtained from McGregor BFA and are in daily observations. Table 3 above shows the breakdown of the daily data which was broken down into four equal cycles, each carrying observations for four different terms, each containing two-year observations and an overall cycle consisting of observations for eight years which is the full study period. This set up was implemented to answer the question of co-integration relationships between selected indices in different time spans or custom periods. This arrangement assisted in assessing if diversification can be achieved by investing in different indices in South Africa. The data set extends from two years before the 'global credit crunch' to the recovery of the financial markets. Therefore the technique of breaking data into four different terms was useful in analysing how the indices related over pre-, during and post-recession periods. The total number of observations amounted to 2 019 daily observations. In addition, the data set for the "segregation method", was to be used to construct roll-over method cycles by adding two-year observation on top of previous two-year observations. This provided a holistic view of the continued linear relationship between the indices in question. The latter strategy also helped to increase the number of observations since co-integration is a long-run occurrence. Table 4 below describes start, end and the number of observations for the roll-over strategy.

Table 4: Daily data cycles (roll-over strategy)

CYCLE	START DATE	END DATE	OBSERVATIONS
1ST 2 YEARS	08-Sep-06	05-Sep-08	500
2nd 2 YEARS	08-Sep-06	07-Sep-10	1000
3rd 2 YEARS	08-Sep-06	07-Sep-12	1502
8 YEAR PERIOD	08-Aug-06	06-Oct-14	2019

This study sought to gain insight into style investing by adopting two objectives. It is important to note that each objective required the use of a different methodology; this is discussed in the following section. Readers are, therefore, reminded that, for the objective of style drift, weekly data was used because the model for style drift requires a minimum of 61 observations. For the objective of long-run relationship, daily data was collected. Again, this is because of the number of observations that needed to be included in the model in order to obtain reliable and efficient results.

Table 5 below tabulates the names of the mutual funds used in this study. Four mutual funds were sampled that track selected six South African indices. As noted earlier, FUNDS A and B are the top performers and FUNDS C and D are the bottom performers per index.

Table 5: List and description of mutual funds used

INDICES	FUND A	FUND B	FUND C	FUND D
Large cap	Stanlib ALSI 40 fund class A	Absa large cap fund	Old Mutual top 40 fund A	Momentum top 40 index fund
Small cap	Ned Group investment entrepreneur fund R	Old Mutual small companies Fund R	Stanlib small cap fund class A	Coronation smaller companies fund
Resources	Investec commodity fund class R	Ned Group investment mining and resources fund class R	Stanlib gold and precious metal fund class R	Old Mutual mining and resources Fund R
Value	Investec value fund class R	Element Islamic equity fund A	Cadiz mastermind fund class A	Marriott dividend growth fund class R
Growth	Foord equity fund	Sim top choice equity fund A	Investec growth fund class A	Ned Group investment growth fund A
Industrials	Coronation industrials fund class A	Stanlib industrial fund class A	Momentum industrial fund A	Stanlib industrial fund class R

Different classes of units arise when a manager wants to apply different charges to different types of investors. The difference between Class A and Class R is based purely on the fees charged by fund managers; it does not have anything to do with asset allocation and investment mandates.

3.3 Methodology

This study aimed to assess asset allocation and co-integration among selected South African indices. While these are two very different objectives, they are linked and analysed together to describe possible diversification patterns. Therefore, two different methodologies are outlined and explained in this section. Firstly, the study used the Engle-Granger two-step procedure to test for long-run relationships between six South African indices. Secondly, it used the return-based style analysis (Sharpe, 1992), asset class factor model to test for style drift. The following section describes the methods and models used in this study in detail, starting with the co-integration methodology.

3.3.1 Co-integration

Co-integration is a measure of the long-run relationship between variables. When variables are found to be co-integrated, it is concluded that they share long-run relationships. They also trend together and share similar behaviour in the long-run. The results of co-integration have direct implications for the concept of diversification. In return, diversification ensures proper risk management and return maximization (Anderson et al., 2009). Since co-integrated variables share a similar trend in the long-run, individuals and investors cannot diversify their portfolios by using co-integrated variables because they behave in a similar manner. If variables appear to have different long-run trends and behaviour, it means that they cannot stay in a fixed long run-relationship, suggesting that they cannot model the long-run (Sjö, 2008).

One of the questions this study set out to answer is the level of diversification that can be achieved between South African styles. It therefore sought to answer this question using co-integration methodologies. The following sub-sections provide detailed information on the methods used to study the co-integration relationship of selected South African indices.

3.3.1 (A) Unit root methodology

When modelling long-run relationships, especially when working with financial data, it is important that the behaviour and properties of the data in question are known (Sjö, 2008, Brooks, 2008). These properties may range from stationary to non-stationary. Each property has its own implications and measure that can be used to adjust for the unwanted attribute in the data. To obtain accurate and meaningful results, it is important to ascertain if data is stationary or non-stationary before running quantitative and statistical models. To be more precise, it is crucial to ascertain the integration order of the series since it is used to set up models (Sjö, 2008). Stationary data series, are desirable property, are defined as data that possess constant auto-covariance, constant mean and constant variance for each lag (Brooks, 2008).

The stationarity or otherwise of financial data series plays a significant role in determining the behaviour variables in question. A typical example is when variables experience external shocks (Brooks, 2008). This shock can stay in the system forever, can gradually decline and can gradually increase over time. A best model or data series is when the variables used do not store shocks forever but eliminate them as time passes. In such a case, stationary data is obtained. The use of non-stationary data in any financial or statistical model runs the risk of obtaining inaccurate, false and un-interpretable results (Brooks, 2008, Sjö, 2008).

The Augmented Dickey-Fuller (ADF) test is used to test for stationarity or otherwise in data series with the aid of the following equation:

$$\Delta y_t = \alpha_1 + \alpha_2 t + \delta y_{t-1} + \sum_{i=1}^{h} \beta_i \Delta y_{t-1} + \varepsilon_t \qquad EQ\ 2$$

In equation 2, y_t represents the variable in question at any point in time and *t* represents time index. α is the intercept constant called drift, t is the time variable, often referred to as trend variable. δ is the focus of the test representing the coefficient process root. β_i is the coefficient on time trend and ε_t represents independently distributed residuals and h is a static term (Gujarati and Porter, 2009a).

In the above equation, the null hypothesis is $\mathrm{H_0}: \delta = 0$ (i.e., variable is not stationary), against $\mathrm{H_1}: \delta < 0$ (i.e., variable is stationary). If the variable is stationary at level, it is called I(0) series. If the variable becomes stationary after being differenced once, it is called I(1) series.

The main idea behind the ADF test is to investigate the effect of previous shocks on current value. Nevertheless, the ADF test is suspect when the sample period includes major events like oil shocks and depression (Gallo et al., 2007). Failure to consider it properly can lead to erroneous conclusions where the null hypothesis is improperly rejected or not rejected. It was expected that this test would be successful in this study since South Africa did not experience any extreme event in the period covered, with the exception of the 2008 financial crisis which was felt worldwide.

This test is mainly conducted on variable δ. Should this variable be greater than zero i.e., $\delta > 0$, the variables need to be differenced. This means that if variables suffer from random shock, it will not die away but will gradually increase over time, rendering the series open to the possibility of overestimating figures.

The second scenario is when variable δ is equal to zero, i.e., $\delta = 0$. This is an undesirable property because it means that, should the variables suffer from external shock, this shock will not die away, nor will it grow but it will remain in the system forever (Brooks, 2008). Therefore, the data will need to be differenced in order to make it stationary.

The third case is when δ is less than zero i.e., $\delta < 0$. This is a desirable property. The data need not be differenced because it is stationary. This means that if variables suffer from a shock, this shock will gradually die and eventually be permanently removed from the system (Brooks, 2014). With this kind of data, a true and accurate representation of data is obtained.

For robustness check, the study utilized the Phillips-Perron (PP) test of stationarity. This test uses a nonparametric statistical method to control for serial correlation in the error terms without adding lagged difference terms (Gujarati and Porter, 2009b).

3.3.1 (B) Engle-Granger's two-step procedure

Among several tests of co-integration that can be estimated, the Engle-Granger's two-step procedure is used to further confirm and pinpoint where the co-integration lies. This model was formulated by Engle and Granger in 1987. It holds power and added advantage because it is deemed the most intuitive model which is easy to perform (Sjö, 2008). However, like any other financial and statistical model, this test has its own shortfalls. Therefore, other co-integration methodologies were created and utilized (Sjö, 2008). There are newer models that test for co-integration, one of which is the Johansen test. This test also has advantages and disadvantages. There is an unresolved debate on which model performs the best when a different time span and frequency are used. One of the major drawbacks of this model is that it has lower power when dealing with a restricted short sample (Zhou, 2001). Circumventing the lower test power of the Johansen test of co-integration for a restricted data sample, and given that the data sample for this study is restricted this study employed the Engle-Granger test of co-integration despite it being an older model. Regardless of recent innovations and additions to financial data models, the Engle-Granger test of co-integration is used quite often in the literature when the researcher is faced with a limited data sample (for example, Alam (2011); Aktaş and Yilmaz (2012); Asche et al. (2012); Subha and Nambi (2013); and Yüksel and Güleryüz (2015)).

High frequency data was used after Zhou (2001) advocated that for a short time span, modelling and test power could be compensated for by increasing data frequency. In this study daily data was used to boost the test power of the co-integration methodology since the study period was restricted. It is noted that increasing the sample span offers more gains in testing power than increasing data frequency. One of the ways to increase the time span for the models is to implement a roll-over strategy. However, this strategy could not be implemented in this study as it sought to compare co-integration relationships between indices and asset allocation at the same time. Therefore, implementing a roll-over strategy would cause co-integration relationships to be influenced by old observations, and subsequently make the co-integration results incomparable to asset allocation since asset allocation analysis is only conducted on segregated periods. It is for this reason that asset allocation and co-integration data input were divided into different terms to allow for comparison within fixed periods of time.

The Engle-Granger model can be represented using the following equation:

$$x_{1,t} = \beta_1 x_{2,t} + \cdots + \beta_p x_{p,t} + u_t \qquad EQ\ 3$$

In the above equation, *p* is the number of variables in the equation. The model stresses that all variables included be integrated to the same order, i.e., integrated in first order, which means that the original data was stationary after being differenced once *I(1)* or *I(2)*. The residual term of this equation is represented in the following equation:

$$u_t = x_{1,t} - \beta_1 - \beta_2 x_{2,t} - \cdots - \beta_p x_{p,t} \qquad EQ\ 4$$

The term u_t is the residuals of variables included in the equation denoted by *p*. The model assumes that all variables included in the equation are I(1).

Usually, this equation represents economically meaningful equations or any understandable equation that can be interpreted with ease (Sjö, 2008). If the variables in question are co-integrated, they will share a common long-run trend and form a stationary relationship in the long-run (Sjö, 2008, Gujarati and Porter, 2009a, Brooks, 2014).

The second step of the Engle-Granger two-step model is to test for unit root on the residuals obtained from the first step. ADF is again used to serve this purpose. The ADF test follows the same equation used above in the unit root methodology.

The estimated residuals will be of the same order as the variables used in step one. Moreover, the lag length must be estimated with caution since it is mandatory for the residual process to be a white noise process. The null hypothesis is no co-integration. Should the null hypothesis be rejected in favour of the alternative hypothesis, this will lead to the conclusion that the variables are co-integrated and trend together in the long-run. Unlike the normal ADF test for variable stationarity, it is important to note that, with this model, co-integration leads to a stationary *I(0)* residual (Sjö, 2008, Brooks, 2014).

As stated above, this model suffers from some shortfalls. Firstly, the second step of the model involves testing stationarity using the ADF model. Therefore, all the problems associated with the ADF test are inherited in this model (Sjö, 2008). Second, the model is constructed on the assumption of one co-integrating vector captured by the co-integrating regression. It is, therefore, necessary to be alert when adding many variables as this may not change the outcome of the test. Third, "*if some variables do not belong in the co-integrating vector, OLS estimation will simply put its parameters to zero, leaving the error process unchanged*" (Sjo, 2008: 11). To avoid this problem, bivariate testing is recommended (Sjö, 2008).

Before running any co-integration models, it is of the utmost importance that the properties carried by data use are known and adjusted accordingly, if required. Data must be non-stationary at levels, but becomes stationary when differenced once, i.e., stationary at *I(1).* Furthermore, all variables must be integrated to the same order, i.e., all variables must be *I(1).*

Due to the latter recommendation, a bivariate test was conducted for each index involved in this study against all other indices. By doing this, a clear picture of which indices are co-integrated or otherwise was obtained. The Engle-Granger two-step procedure is a helpful tool in a study of this kind because it gives a clear indication of co-integration, unlike other tests which estimate the number of co-integrating vectors and do not specifically pinpoint the co-integrating vectors or equations (Sjö, 2008).

The study mainly focuses on funds' returns and tracking ability of selected funds against long run relationship of tracked indices. Therefore, any co-integrating relationship found is interpreted as the factor that is decreasing the benefits of diversification from the investors' perspective. In contrast, no co-integration is an advantage and good news for investors.

As stated in the data section, the data was broken down into four equal terms each carrying +500 observations (refer to Table 3). To test for co-integration, six indices found within the South African stock market were used. Subsequently, a complete co-integration test consisting of 2 019 observations for the full period of eight years was estimated. This provided a holistic view of co-integration between selected indices in an eight-year horizon. Furthermore, a co-integration test was run on all different terms to determine how the relationship between indices changed over time.

Finally, to further investigate the trending relationship between the aforementioned indices, correlation matrixes were established for the purpose of analysing short-run behaviour. This method use returns instead of raw data used for other tests. To make the results meaningful, the following widely accepted thresholds were used. Where the correlation coefficient (r) is between

- 0.76 to 1.00 = strong/high positive relative correlation
- 0.51 to 0.75 = medium/moderate positive correlation
- 0.25 to 0.50 = low/weak positive correlation
- Under 0.25 = trivial

The correlation methodology was conducted on both segregated periods and roll-over methods. This methodology was employed to answer the question of short-run relationships between selected indices throughout the study period.

3.3.2 Asset class factor model

This study used the Sharpe (1992) factor model to test and answer the question of style drift in South African mutual funds. A factor model on each fund was run and checked for tracking ability and the possibility of style drift. The 427 weekly observations were broken down to form seven different terms, each made up of 61 observations, as shown in Table 1. The number of terms (seven) offered a wide enough time frame to scrutinize how each fund behaved over time and search for any style drift. Moreover, the asset class factor model allowed the researcher to identify if managers controlled for style drift or simply deviated for extended periods to capture side returns other than those suggested by the fund mandate (name). The R-squared tests were conducted to confirm the efficiency of the asset class factor model in modelling the collected data.

Generally, the South African stock market indices overlap with some shares found in more than one index. For example, the industrials and top 40 indices may contain the same stocks depending on the stock's market capitalization. However, this study did not implement any measures to circumvent repetition of shares in different indices. Indices were taken as they were and regressed against selected tracking funds as per the mutual funds database. This was simply because the study aimed to examine the level of diversification and opportunities from the retail unit trust investor's perspective. When these investors invest their funds, they invest in the market as it is where there are share repetitions as, unlike institutional investors, they do not impose an investment mandate on fund managers. It is therefore easy for institutional investors to control and stop portfolio managers from investing in indices with large repeated stocks or stipulate any restrictions. Sadly, retail investors do not have this option. It is therefore important to use indices as they are since investors invest in them as they are. The study sought to compare like for like. The reconstruction of indices would create a completely different, partial or conceptual environment from what retail investors are actually exposed to when investing in mutual funds.

The Sharpe (1992) factor or linear model has been used a number of times in the literature and is still recognised as the best model to investigate tracking ability (Arezki et al., 2014). Thus, this study borrowed this model to test or check the direction of each fund in order to separate them and confirm their ability to follow the proposed mandate, i.e., large cap, small cap, resources, value stocks, growth stocks, resources and industrial stocks. After confirming which fund responded to which asset class (style), the study further investigated the possibility of style drift by examining its tracking ability from the first term, i.e., term 1 moving to the last term, i.e., term 7.

Sharpe (1992) states that asset allocation entails a vast amount of variability in total returns on a single investor's portfolio. This is because a single portfolio consists of many different assets and funds which may contain a number of securities. Once portfolio managers are certain on which asset class they are going to invest in, it is crucial that they determine the rate of exposure of each component to movements in their returns. This is widely accepted as explained by "beta". Beta is used to check for tracking ability. Changes in beta pronounce changes in tracking ability and mandate.

It is widely accepted in the financial literature that financial data and returns can be efficiently modelled using the following equation (Brooks, 2008):

$$y_t = \alpha + \beta x_t + \mu_t \qquad \text{EQ5}$$

In the above equation, y_t is the dependent variable, x_t is the explanatory variable, β is the coefficient of x_t and represents the relationship between x_t and y_t. α is alpha and μ_t represents residuals.

Equation 5 is called the population regression function. It is regarded as one of the best models for modelling financial data and conveys the true relationship between variables. Brooks (2008) also describes this model as a data generating process. The model includes variable μ_t which is known as disturbance or error term. This term captured data that was not detected by the true regression variables, i.e., x_t and y_t. β symbolises the strength of the relationship between the explanatory variable and dependent variable.

Equation 5 may depict returns on single assets to capture the returns on all asset classes at once. Sharpe (1992) formulated the following equation which is an advanced version of equation 5 in the sense that it reveals the rate of return that a single asset in a portfolio contributes to total returns:

$$\widehat{R_i} = [b_{i1}F_1 + b_{i2}F_2 + \cdots + b_{in}F_n] + e_i \qquad \text{EQ 6}$$

In equation 6, R_i denotes the return on asset i. F_1 to F_n denote the value of factor 1 to the last (n-th) factor, keeping in mind that, in this case, a factor describes an asset class. Therefore, one can say that F_1 to F_n represent asset class 1 to asset class n. The right hand side of this equation represents the total returns on the portfolio while the left hand side represents the returns contributed by every style in that portfolio.

In this study, the asset class factor model is expressed as the following equation:

$$\widehat{R_i} = [b_1 value + b_2 growth + b_3 largecap + b_4 smallcap + b_5 industrials + b_6 resources] + \varepsilon_i \qquad \text{EQ 7}$$

In the equation above, b_1 represents the relationship between asset R_i returns and returns on the value index. b_2 represents the relationship between asset R_i returns and returns on the growth index. The same is true for large cap moving to the last factor "resources".

Wermers (2010) presented a complete method of measuring style drift called "holdings based style drift measure". This method provides a detailed report since it measures style drift to any possible dimension. This method is also called the "characteristics based approach". It aims to examine a portfolio manager's performance by examining the characteristics of his/her composite portfolio in relation to the target benchmark (Moore, 2013). These characteristics may range from price to earnings ratio, to dividend yield, and market to book ratio. Furthermore, it classifies and separates drift that is due to active trading and drift due to passive holding strategy. Thus, this model reports on induced or intentional drift and drift that is beyond the control of the manager such as that related to passively holding stocks that keep changing their characteristics. This method is based on the notion that there are three dimensions that a style drift may possibly take: "market capitalization" (relating to small-cap, mid-cap, and large-cap style), industry adjusted "book to market" (relating to value and growth style), and price momentum (relating to momentum contrarian style). The holdings-based approach suffers from no constraints or limitations and requires subjective judgment to group characteristics in order to define a specific management style (Moore, 2013).

In contrast to Wermers (2010) portfolio-based methodology, this study employed the asset class factor model in equation 7 to test for style drift. It borrowed the factor model as opposed to Wermers' methodology because the return-based model requires less information on the composition of the portfolio under examination (Moore, 2013). Furthermore, this method requires fewer subjective judgements and is able to be used efficiently in the performance measurement. However, the factor model would still enable the detection of the direction of the drift. As in Sharpe (1992), multifactor models were used to perform return-based style analysis. The returns on the funds were analysed with reference to a set of style-based explanatory factors which aimed to explain the maximum amount of deviations in the funds' returns over the analysed period. As demonstrated in Ter Horst et al. (2004), these factors are often the returns on several factors or benchmark portfolios, such as value, growth, small cap, momentum, country or sector portfolios. In this case, the factors were the aforementioned six South African indices found on the JSE.

The asset class factor model was run on a constructed terms basis and recorded all betas which represent fund sensitivity. After recording betas, a regression of weekly returns for the next term was done. This was rolled from the first term of the study period until the very last term which sits at 6th October 2014. In so doing, a clear picture was obtained of which funds changed direction through shift to a certain style and the corresponding move away from a certain style. This is best described as style drift, the propensity of fund managers to change from one style to another (Wermers, 2010). Style drift can be investigated better using Wermers (2010) "holding based method" and "Microsoft solver computer package". Nevertheless, this study used the return-based measure of style investing. By implementing this method, patterns of style investing and style drift from the funds' past returns over a desired period of time were derived (Sharpe, 1992). The factor model was employed in order to avoid using many different models when it is possible to deliver relevant and accurate results in one run.

All models, i.e., ADF, co-integration models and the asset class factor model, were performed on E-views version 6.

3.4 Chapter summary

This chapter presented a detailed discussion on the methods used to fulfil the two objectives of the study outlined in Chapter 1. The Engle-Granger two-step procedure and the asset class factor model were employed to answer the research questions which were also presented in Chapter 1. The type of data frequency used was clearly explained, i.e., daily data for the Engle-Granger two-step approach and weekly observations for the asset class factor model. Both sets of data were obtained for a period of eight years from 2006 to 2014. This period also contained observations for 2007 when there was a global financial crisis. Hence, this study was expected to deliver interesting results which cover the pre- and post- global financial crisis period.

The following chapter presents the results of this study.

CHAPTER 4: RESULTS

4.1 Introduction

This section presents the results obtained after filtering the data described in the previous section into the models identified and explained in Chapter 3. The methods were arranged in the following order:

- ADF unit root test; coupled with PP unit root test for robustness purposes
- Engle-Granger two-step procedure co-integration test; and
- asset class factor model.

Each model was run separately and the results were tabulated in the custom tables which are displayed in this section for ease reference. The original tables obtained from E-views version 6 are provided in Appendices B and C.

4.2 Co-integration results

To test for co-integration, the unit root test was conducted to establish whether each series is integrated of I(0) or I(1). As described in Chapter 3, if a series is integrated of I(0), the series is stationary at level. However if a series is integrated of I(1), the series is stationary after being differenced once.

4.2.1 Unit root test

Table 6 below shows a summary of the results obtained in the ADF test. The full results obtained from E-views are included in Appendix B. The null hypothesis is that each variable is non-stationary and the alternative hypothesis is that variable is stationary. The test was conducted for the eight-year sample, using daily data, as described in Chapter 3. The total number of observations amounted to 2 019. The ADF test enabled intercept and trend to be accounted for in line with Kasibhatla et al. (2006) recommendations.

Table 6: ADF Unit root results

UNIT ROOT	LEVEL				1st DIFFERENCE			
	P VALUE	CRIT VALUE	Tau STAT	N H	P VALUE	CRIT VALUE	Tau STAT	N H
Large cap	0.7145	-3.4120	-1.7796	fail to reject	0.0000	-3.4120	-44.6791	reject
Small cap	0.9937	-3.4120	-0.1670	fail to reject	0.0000	-3.4120	-37.7999	reject
Resources	0.1556	-3.4120	-2.9219	fail to reject	0.0000	-3.4120	-42.7059	reject
Value	0.6302	-3.4120	-1.9449	fail to reject	0.0000	-3.4120	-44.3961	reject
Growth	0.7772	-3.4120	-1.6394	fail to reject	0.0000	-3.4120	-43.9120	reject
Industrials	0.8757	-3.4120	-1.3467	fail to reject	0.0000	-3.4120	-44.3940	reject

* MacKinnon (1996) one-sided p-values.

CRIT VALUE= critical value at 5% level of significance, NH= null hypothesis outcome

The results show that the null hypothesis cannot be rejected at level and hence the variables are not stationary at level. Further tests conducted at 1st difference proved otherwise, where the null hypothesis was rejected. The tests concluded that all the variables used are stationary after being differenced once. The series is therefore, integrated of I(1), suggesting that the variables could be co-integrated. The ADF results at levels and first differences of the series showed very high *p*-values and low *p*-values, respectively, thus implying overwhelming support of the data being integrated of order I(1), Nevertheless, the Phillips-Perron (PP) stationarity test was conducted for robustness check. This test uses a nonparametric statistical method to control for serial correlation in the error terms without adding lagged difference terms (Gujarati and Porter, 2009b). Since the asymptotic distribution of the test is the same as the ADF test, the PP test therefore shares the same statistical values as the ADF test. The PP test further confirms that series are integrated of order I(1). The results from PP output are recorded in Table 7 below.

Table 7: Phillips-Perron Unit root results

UNIT ROOT	LEVEL				1st DIFFERENCE			
	P VALUE	CRIT VALUE	T STAT	N H	P VALUE	CRIT VALUE	T STAT	N H
Large cap	0.8172	-3.4120	-1.5357	fail to reject	0.0000	-3.4120	-45.1006	reject
Small cap	0.9807	-3.4120	-0.5594	fail to reject	0.0000	-3.4120	-40.5085	reject
Resources	0.1593	-3.4120	-2.9101	fail to reject	0.0000	-3.4120	-42.6952	reject
Value	0.7373	-3.4120	-1.7309	fail to reject	0.0000	-3.4120	-44.6840	reject
Growth	0.8331	-3.4120	-1.4898	fail to reject	0.0000	-3.4120	-44.0852	reject
Industrials	0.8772	-3.4120	-1.3410	fail to reject	0.0000	-3.4120	-44.3940	reject

4.2.2 Engle-Granger two-step procedure (long-run relationship)

In this study, all tests were conducted only at the 5% level of significance. This is in line with the study by Gallo et al. (2007). This level of significance was selected due to the need for precision when investigating funds that are located within the same economy/market as they are likely to behave in the same way because they suffer from the same external and internal economic shocks. These tests were conducted using daily frequency which was further divided into four equal parts, each covering a two-year period. This was done to enable the study to capture continuous behaviour and long-run relationships between selected indices. The stationarity tests found that all variables are non-stationary at level but become stationary at 1st difference. Therefore, they are all integrated to the same order, i.e., I(1), and the Engle-Granger two-step procedure was performed.

The results of the bivariate Engle-Granger procedure are summarised in Table 8. Panel A tabulates results for the first two years. Panels B to D tabulate results for the second two years to fourth two years, respectively, and panel E tabulates results for the overall period of eight years. The null hypothesis (N H) is: H(0), variable are I(1) or no co-integration. H(1), variables are I(0) or co-integrated.

Table 8: Bivariate/Engle-Granger two-step approach results (segregated period)

	Panel A		Panel B		Panel C		Panel D		Panel E	
	FIRST 2 YEARS		SECOND 2 YEARS		THIRD 2 YEARS		FOURTH 2 YEARS		8 YEAR PERIOD	
SERIES TESTED	T STAT	N H OUTCOME	T STAT	N H OUTCOME	T STAT	N H OUTCOME	T STAT	N H OUTCOME	T STAT	N H OUTCOME
Small cap/industrials	-3.7279	**Reject**	-4.6972	**Rejected**	-4.7727	**rejected**	-2.8947	fail to reject	-4.4339	**rejected**
Small cap/resources	-1.6217	fail to reject	-3.8610	**Rejected**	-2.2274	fail to reject	-1.8593	fail to reject	-1.1189	fail to reject
Small cap/large cap	-1.4817	fail to reject	-4.5430	**Rejected**	-3.8876	**rejected**	-3.0202	fail to reject	-4.0088	**rejected**
Small cap/growth	-1.5270	fail to reject	-5.1356	**Rejected**	-4.2001	**rejected**	-3.1359	fail to reject	-4.0213	**rejected**
Small cap/value	-2.0584	fail to reject	-3.1643	fail to reject	-3.4769	**rejected**	-3.1078	fail to reject	-1.9662	fail to reject
Industrials/resources	-2.1449	fail to reject	-2.8358	fail to reject	-2.3324	fail to reject	-1.8463	fail to reject	-1.5628	fail to reject
Industrials/large cap	-1.9527	fail to reject	-2.9276	fail to reject	-2.5050	fail to reject	-2.0042	fail to reject	-3.0111	fail to reject
Industrials/growth	-2.1005	fail to reject	-3.4517	**Rejected**	-2.8390	fail to reject	-2.1382	fail to reject	-3.2874	fail to reject
Industrials/value	-1.7351	fail to reject	-2.7804	fail to reject	-2.0172	fail to reject	-1.8619	fail to reject	-2.1821	fail to reject
Resources/large cap	-2.7150	fail to reject	-3.4924	**Rejected**	-3.3340	fail to reject	-1.7318	fail to reject	-3.1964	fail to reject
Resources/growth	-2.5459	fail to reject	-2.4561	fail to reject	-3.4025	**rejected**	-1.7090	fail to reject	-2.9184	fail to reject
Resources/value	-2.3221	fail to reject	-4.0501	**Rejected**	-3.4509	**rejected**	-1.8585	fail to reject	-3.2190	fail to reject
Large cap/growth	-3.1429	fail to reject	-3.3258	fail to reject	-2.3962	fail to reject	-4.3593	**rejected**	-3.1156	fail to reject
Large cap/value	-2.0036	fail to reject	-4.2784	**Rejected**	-2.7287	fail to reject	-3.1792	fail to reject	-1.8759	fail to reject
Growth/value	-2.7326	fail to reject	-4.0211	**Rejected**	-1.7469	fail to reject	-3.5362	**rejected**	-2.0540	fail to reject

Engle and Yoo (1987), *EG Critical value **5%= -3.37**, EG Critical value at **10%= -3.02**

The Engle-Granger results for the first two years, which run from 08-SEP-2006 to 05-SEP-2008, show that there is only **one** co-integrating equation running between small caps and industrials, as shown in panel A. Using a bivariate Engle-Granger two-step procedure, a significant relationship with a *T*- value of -3.7279 was obtained. This value confirms that these two indices are co-integrated at the 5% level of significance.

Moving on to the second term, which runs from 08-SEP-2008 to 07-SEP-2010, the same procedure of using daily data for the period of two years was implemented. These results show a drastic change compared to the results of the first two years. Here, there were a total of **nine** co-integrating relationships, as shown in panel B, compared to **one** obtained in the previous term. The following indices were found to be co-integrated at the 5% level of significance:

- small caps and industrials;
- small caps and resources;
- small cap and large cap;
- small cap and growth;
- industrials and growth;
- resources and large caps;
- resources and value;
- large caps and value; and
- growth and value.

Of all the reported co-integrating relationships, it is worth noting that the repeat of the long-run relationship between small caps and industrials was also significant in the first two years. These results show that the South African funds industry is very fragile and susceptible to drastic changes in a period of less than two years. This proves to be the more unsecured timeframe of investing within the funds industry or between selected indices. This horizon saw only **six** non co-integrated combinations out of a possible 15.

The third two-year period from 08-SEP-2010 to 07-AUG-2010 shows a huge improvement in the diversification level and strategies of diversification that can be implemented and attained. This term recorded **six** co-integrating relationships compared to **nine** in the previous term. Notably, the relationship between small caps and industrials still holds. This relationship ran from the first to the third term. Small caps and value previously reported a non-co-integrated relationship; however, they proved to be co-integrated in the third term.

These two indices were also not co-integrated in the first term. Again, this serves as evidence of how this industry is subject to change. What was not co-integrated two years ago may be perfectly co-integrated in the following year.

The last term, the fourth two years which sits in the time frame when this study was conducted, delivered another unexpected result. This term, which runs from 08-SEP-2012 to 06-OCT-2014, recorded only **two** co-integrated relationships lying between:

- large cap and growth, which becomes co-integrated for the first time in this study; and
- growth and value which become co-integrated for the second time in the space of eight years.

At the beginning of this study, it was expected that growth and value would not as they are be co-integrated as they are considered “style and twin”. However, the results show that the relationship between these two indices keeps changing from being not co-integrated, which is desirable, to co-integrated, and not co-integrated again to co-integrated. Since they started to be co-integrated during the second term, were unrelated in the third term and were co-integrated again in the last term, the eight-year period was examined to establish whether these indices still have a long-run relationship. The results show that they are not co-integrated with a *T*- value of -2.0540. Having said this, it is important to consult the shortened sample before making any judgement and creating a portfolio.

By breaking the data into short periods of as little as two years but wide enough to satisfy the requirements of observations in the models, a clear picture of the fragility and instability of this industry was obtained. If long-run relationship was tested using the eight-year period data only, the study would have missed how these indices kept changing relationships between each other. The results for the entire eight-year period reported only **three** co-integrated relationships which were found between:

- Small caps and industrials;
- Small caps and large caps; and
- Small caps and growth.

The results obtained from the eight-year period term confirm the overall outcome of the study. A repeated co-integrated relationship between small caps and industrials, small caps and large caps and small caps and growth was observed i.e. (Panel B and C) and their co-integrating relationships were further confirmed in the eight-year period sample, which averages all other terms (Panel E).

4.2.3 Short-run relationship

For the purpose of evaluating short-run relationships between the selected sectorial indices, the tables in appendix D, 7.4.1 tabulate correlation coefficients and p-values for all six selected South African indices. The results show that, during the first two-year period, all indices were correlated and most correlation coefficients were extremely high, substantiating near directly proportional relationship. The possible explanation could be that these indices share a large amount of the same stocks or they operate within the same economy which subjects them to the same economic or financial shocks. Notably, the short-run relationship between small cap and resources was low (0.469743) but positive and significant with a p-value of 0.0000. Also in this term, correlation coefficient for resources and industrials recorded a low value of 0.478557. The second two-year term recorded high correlation between all indices. Recall that this term also recorded the highest number of co-integrated indices from the segregated long-run relationship analysis above. Such strong long-run and short-run relationships can be attributed to the fact that this term contains observations from a global recessionary term. The lowest correlation coefficient (0.469743) was between small cap and resources.

The third two-year period also recorded high correlations between the six selected funds; however, correlation coefficients were weaker than in the previous term. This time frame also saw low correlation between small cap and resources. Small cap and resources and industrials recorded a significant value of (0.472932), small cap and growth recorded a value of (0.489969) and finally, small cap and large cap stated a value of (0.486889). During the fourth two-year and the eight-year overall period, the short-run relationship between the six selected South African indices strengthened; however, the four previously low correlated sets, i.e., (resources/industrials), (small cap/resources) continued to recorded low but positive correlation coefficients.

Given that these indices operate within the same economy, it is no surprise to witness high correlation between them. Looking at short-run relationships from the beginning of the data sample, the first two years, to the overall period, some indices sets prove to be less correlated. These sets are: (resources and industrials), (resources and small cap) and (resources and value). Using short-run relationships to allocate assets, one would then be advised to allocate across these less-related indices in order to realise the benefits of diversification. However, this method suffers from the many shortcomings mentioned above, and one cannot merely rely on short-run results to make long-run decisions.

4.2.4 Long-run relationship (roll-over strategy)

Table 9 below displays the co-integration relationship results between the selected six JSE indices when the roll-over method was used. It is noticeable that, the values in Table 8 differ from those in Table 9 because of the difference in the number of observations since the latter implements the roll-over strategy. This strategy was used to increase the number of observations in a single cycle since co-integration is a long-run phenomenon and also to gain better insight into how these indices were linear or continuously related.

Comparing the results in Tables 8 and 9, we find that, by adding observations through the roll-over strategy, the co-integration relationship changes drastically. *T*- values from panel B of Table 8 are closer to the significant region, while *T*- values from panel B of Table 9 are far from being significant at 5% level of confidence interval. This is because panel B of Table 9 contains diluted observations from pre- and mid-recessionary period observations. As suggested above, the high rate of co-integration in the second two years is due to observations which only came from the recessionary period, when indices are subjected to the same economic turmoil, pressure and difficulties.

Table 9 below shows that large cap/growth share a weak relationship which is only significant at 10% in all cycle. The study conducted and accepted hypothesis testing at 5% level of confidence only, but the strengthening relationship between these two indices was noted. Small cap/ industrials are consistently co-integrated throughout the study period. Moreover, the relationship intensifies as time goes by; *T*- values increase from the first cycle to the third cycle. These findings are comparable with those recorded when the segregation strategy was implemented, where this pair was co-integrated four times out of five at 10% confidence interval. Industrials/ growth *T*- values also strengthens until they reached -3.2874, which is only significant at 10% but not at 5% confidence interval. Despite the fact that we do not regard these two indices as co-integrated since we only accept at 5% confidence interval, it is noted that the relationship is becoming stronger over time. Thus, this pair should perhaps be observed carefully as they promise to converge closer to each other. This pair behaves like small cap/growth and small cap/ value pairs.

The results from both the segregated and roll-over methods recorded a co-integrating relationship between small caps and industrials and the relationship is strong as shown by largely significant *T*- value of -4.4339. Interestingly, *T*- values of (small cap/large cap) and (small cap / growth) pairs decrease over time and finally settle by being co-integrated in the eight-year period results.

Table 9: Engle-Granger two step approach results (Rollover)

	Panel A		Panel B		Panel C		Panel D	
	FIRST CYCLE		SECOND CYCLE		THIRD CYCLE		8 YEAR PERIOD	
SERIES TESTED	T STAT	N H OUTCOME	T STAT	N H OUTCOME	T STAT	N H OUTCOME	T STAT	N H OUTCOME
Small cap/industrials	-3.7279	**rejected**	-4.4989	**rejected**	-4.6498	**rejected**	-4.4339	**rejected**
Small cap/resources	-1.6217	fail to reject	-1.5490	Fail to reject	-1.0094	fail to reject	-1.1189	fail to reject
Small cap/large cap	-1.4817	fail to reject	-2.3718	Fail to reject	-2.9713	fail to reject	-4.0088	**rejected**
Small cap/growth	-1.5270	fail to reject	-2.1756	fail to reject	-3.0215	fail to reject	-4.0213	**rejected**
Small cap/value	-2.0584	fail to reject	-2.7935	fail to reject	-2.4813	fail to reject	-1.9662	fail to reject
Industrials/resources	-2.1449	fail to reject	-2.1315	fail to reject	-1.1339	fail to reject	-1.5628	fail to reject
Industrials/large cap	-1.9527	fail to reject	-2.4572	fail to reject	-2.1714	fail to reject	-3.0111	fail to reject
Industrials/growth	-2.1005	fail to reject	-2.3316	fail to reject	-2.5998	fail to reject	-3.2874	fail to reject
Industrials/value	-1.7351	fail to reject	-3.1291	fail to reject	-1.6574	fail to reject	-2.1821	fail to reject
Resources/large cap	-2.7150	fail to reject	-1.6712	fail to reject	-2.0013	fail to reject	-3.1964	fail to reject
Resources/growth	-2.5459	fail to reject	-2.5530	fail to reject	-1.3423	fail to reject	-2.9184	fail to reject
Resources/value	-2.3221	fail to reject	-1.7243	fail to reject	-2.6664	fail to reject	-3.2190	fail to reject
Large cap/growth	-3.1429	fail to reject	-3.0231	fail to reject	-3.2666	fail to reject	-3.1156	fail to reject
Large cap/value	-2.0036	fail to reject	-1.6712	fail to reject	-2.6845	fail to reject	-1.8759	fail to reject
Growth/value	-2.7326	fail to reject	-2.1169	fail to reject	-2.7736	fail to reject	-2.0540	fail to reject

Engle and Yoo (1987) *EG Critical value 5%= -3.37, EG Critical value at 10%= -3.02

The tables in Appendix D, 7.4.2 tabulate correlation coefficients for the roll-over strategy which are not much different from those of the segregated period since the first and last term have the same coefficient. Notably, when the roll-over strategy is used, the correlation coefficients are lower. Evidence of this occurrence is provided by comparing the "second 2 years" which was obtained using the segregated period method, and the "2nd cycle" which was obtained using the roll-over strategy. One possible reason for this is that, the coefficients belong to recessionary times, but when the roll-over strategy is implemented, the correlations of the recessionary period are diluted with correlations where indices behave in different ways and are technically not related. All the correlation coefficients for the segregated period are high but with the roll-over strategy, the following correlation coefficients lie in the medium threshold bracket as discussed in the methodology section:

- resources and industrials (medium)
- resources and small cap (medium)

The same is true for roll-over of the "3rd cycle" correlation coefficients. In this term, the short-run relationship between resources and industrials went from medium to low, while, on the other side, resources and large cap reduced from high to medium. The following short-run relationships from "3rd cycle" were found to lie in the low and medium brackets:

- Resources and industrials (low)
- Resources and large cap (medium)
- Resources and small cap (medium)
- Resources and value (medium).

The 1st term and overall period were not interpreted for the roll-over strategy because the results are the same for both the roll-over and segregated period methods. Interestingly, the results from both methods reveal that the resources indices are not correlated to many indices in the short-run. However this was also the case from the long-run relationship tests. Interpreting these findings from the perspective of a risk adverse investor, it would be advisable to choose a combination of indices that includes resources.

4.3 Style drift (Asset class factor model)

The results for the style drift objective were obtained through the execution of the Sharpe asset class factor model. Sharpe (1992) provides that, for efficient results, 61 observations are necessary and optimal. Consequently, the data was separated into seven terms, each containing 61 weekly observations. The results in Table 10 below show how each fund responded to returns of its style/index and other South African sector indices. One of the primary assumptions used for this objective was that, if funds truly replicate their indices, the behaviour of the fund alone must be related to the behaviour of its parent index (benchmark). This study acknowledges that there will not be a one-on-one relationship between fund and index because an index is made up of many stocks, but there should be a notably positive and significant relationship. The following tables (10-33) display the results for all six indices used in this study against 34 funds.

Values in **BOLD** are significant at the 5% level of significance. Values in ***BOLD*** are non-significant at the 5% level where they are expected to be significant because they are purported to replicate their index.

4.3.1 Small caps results and tables

Table 10: Small cap Fund A; factor model results

SMALLCAPS		term 1	term 2	term 3	term 4	term 5	term 6	term 7
		FUND A (NDBE)	FUND A (NDBE)	FUND A (NDBE)	FUND A (NDBE)	FUND A (NDBE)	FUND A (NDBE)	FUND A (NDBE)
	Beta	-2.5345	-0.7929	-0.8479	-4.1748	-5.1819	-1.1747	-0.6062
Large cap	p value	**0.0013**	0.2579	0.3161	**0.0011**	**0.0003**	0.1306	0.3963
	Beta	0.2882	0.5398	0.3627	0.1166	-0.1416	0.4567	0.227
SMALLCAP	**P VALUE**	**0.0197**	**0.0002**	**0.0009**	***0.4821***	***0.4433***	**0.0004**	**0.0513**
	Beta	0.1611	0.2856	-0.3346	0.0116	0.0041	-0.1918	-0.1406
Resources	p value	0.0641	**0.0352**	**0.0002**	0.9317	0.9738	**0.0056**	**0.012**
	Beta	1.5245	0.3408	0.6836	2.3398	2.9545	0.5178	0.2553
Value	p value	**0.0011**	0.4378	0.1693	**0.0013**	**0.0002**	0.0908	0.3421
	Beta	1.3299	0.1725	0.7996	2.602	3.2031	1.3207	0.9134
Growth	p value	**0.0022**	0.6023	0.1036	**0.0002**	**0.0001**	**0.0235**	0.1006
	Beta	0.1520	0.4089	0.2032	-0.0645	0.0709	0.0113	0.1590
Industrials	p value	0.0645	**0.0003**	0.0798	0.6346	0.6012	0.9033	0.1146

Table 11: Small cap FUND B; factor model results

SMALLCAP		term 1	term 2	term 3	term 4	term 5	term 6	term 7
		FUND B (OMSC)	FUND B (OMSC)	FUND B (OMSC)	FUND B (OMSC)	FUND B (OMSC)	FUND B (OMSC)	FUND B (OMSC)
	Beta	-1.3682	-0.8342	-2.3134	-3.585	-2.0622	-0.6177	-1.2066
Large cap	p value	0.1064	0.1432	**0.014**	**0.0005**	**0.0516**	0.3390	0.1320
	Beta	0.5043	0.6067	0.5191	0.1738	0.4533	0.2336	0.2717
SMALLCAP	**P VALUE**	**0.0004**	**0.0000**	**0.0000**	***0.1926***	**0.0024**	**0.0472**	**0.0366**
	Beta	-0.1275	0.0917	-0.2015	0.079	0.0294	-0.0052	0.003
Resources	p value	0.1854	0.3953	0.0292	0.467	0.7667	0.9345	0.9594
	Beta	0.8054	0.4332	1.5645	1.9727	1.0595	0.3586	0.2378
Value	p value	0.1083	0.2252	**0.0049**	**0.0008**	0.0708	0.2145	0.4260
	Beta	1.0334	0.3471	1.4877	2.1807	1.2279	0.6819	1.1949
Growth	p value	**0.0288**	0.1985	**0.0064**	**0.0001**	**0.0411**	0.2103	**0.0547**
	Beta	0.0829	0.2766	-0.0712	0.0036	0.1542	-0.0370	0.4091
Industrials	p value	0.3597	**0.0024**	0.5667	0.9731	0.1465	0.6767	**0.0005**

Table 12: Small cap FUND C; factor model results

SMALLCAP		Term 1	Term 2	Term 3	Term 4	Term 5	Term 6	Term 7
		FUND C (GDSC)	FUND C (GDSC)	FUND C (GDSC)	FUND C (GDSC)	FUND C (GDSC)	FUND C (GDSC)	FUND C (GDSC)
	Beta	-0.5894	0.3483	3.4313	1.003	-3.7996	-1.7987	-3.4608
Large cap	p value	0.7132	0.6947	0.0695	0.4797	**0.0005**	**0.0164**	**0.0136**
	Beta	0.7526	0.7658	1.0612	0.6285	0.3971	0.4611	0.2839
SMALL CAP	**P VALUE**	**0.0004**	**0.0000**	**0.0000**	**0.0014**	**0.0062**	**0.0003**	***0.1716***
	Beta	0.0242	0.3394	-0.3368	-0.2547	0.0545	0.0598	0.1294
Resources	p value	0.8376	**0.0255**	0.0898	0.1651	0.5389	0.4149	0.1806
	Beta	0.3152	-0.4549	-1.9082	-0.7514	2.1897	0.7458	0.8065
Value	p value	0.7037	0.4564	0.0811	0.3626	**0.0004**	**0.0214**	0.1096
	Beta	0.4562	-0.4023	-1.7727	-0.0416	2.1844	1.4934	2.8343
Growth	p value	0.6406	0.3489	0.0931	0.9564	**0.0006**	**0.0059**	**0.0098**
	Beta	0.0631	0.3875	0.4118	0.1609	-0.169	-0.1149	0.2764
Industrials	p value	0.5836	**0.0097**	0.0924	0.3320	0.1146	0.1940	0.1572

Table 13: Small cap FUND D; factor model results

SMALL CAP		term 1	term 2	term 3	term 4	term 5	term 6	term 7
		FUND D (COSG)	FUND D (COSG)	FUND D (COSG)	FUND D (COSG)	FUND D (COSG)	FUND D (COSG)	FUND D (COSG)
	Beta	-2.5467	-0.9986	-2.9757	-0.0014	-1.3224	-0.2457	-0.9690
Large cap	p value	**0.0135**	0.1525	**0.0162**	0.9988	0.2779	0.6981	0.1860
	Beta	0.3555	0.6728	0.6610	0.5785	0.4929	0.3429	0.3894
SMALL CAP	**P VALUE**	**0.0305**	**0.0000**	**0.0000**	**0.0001**	**0.0044**	**0.0011**	**0.0015**
	Beta	0.0478	-0.0667	-0.4529	0.0045	-0.0137	0.0555	-0.0088
Resources	p value	0.6757	0.6132	**0.0003**	0.9683	0.9050	0.3153	0.8734
	Beta	1.4468	0.7891	1.8693	0.1131	0.8664	0.1850	0.4001
Value	p value	**0.0175**	0.0738	0.1032	0.8457	0.201	0.4582	0.1468
	Beta	1.4359	0.4512	2.1339	-0.1156	0.7032	0.2514	0.9106
Growth	p value	**0.0117**	0.1730	**0.0032**	0.8348	0.3080	0.5921	0.1085
	Beta	0.1154	0.0642	-0.2318	0.0823	0.0722	-0.0263	0.0258
Industrials	p value	0.2873	0.5484	0.1604	0.4699	0.5557	0.7326	0.7997

Tables 10-13 above display the results obtained from the Sharpe (1992) asset class factor model. This model was rolled out from the beginning of the period covered in this study to the end. Betas and *p*-values were used to determine the relationship between each fund and selected indices which were used as factors. The top funds in the sample of small cap funds followed the mandate suggested by the name of the style. They are shown by the values of beta and level of significance. The relationship between small cap mutual funds and the small cap index is positive and significant in most cases. There are only four cases where these small cap funds were unresponsive to changes in the small cap index. The relationship between these two funds and the other indices is significant, especially to resources, value and growth. Notably, a pattern is found that, when these funds prove unresponsive to changes in small cap indices, they become more responsive to value and growth, but this is short-lived.

During terms four and five, FUND A in Table 10 was not tracking its own index. However, it tracked the value index with beta of 2.3398 in term four and 2.9545 in term five. This tracking ability proved valid and significant with *p*-values of 0.0013 and 0.0002 in term four and five, respectively.

In the same terms, i.e., four and five, the same fund also became more responsive to returns of the growth index with tracking ability of 2.6020 in term four and 3.2031 in term five. The relationship was pronounced valid and significant by *p*-values of 0.0002 and 0.001, respectively. From the values provided by beta and *p*-values, the findings show that the relationship became stronger as the investigation moved from term four to term five. The tracking ability grew stronger while the *p*-value showed that the relationship was becoming more significant. In term six, the relationship between FUND A and the value index was terminated. Meanwhile, it remained positive with the growth index but beta was less and the *p*-value proved that the relationship was fading away but was still significant. The relationship became statistically insignificant in term seven.

FUND B, in Table 11, displayed almost the same tracking ability as FUND A except that this fund started tracking growth and value indices in terms three to four, finally cutting off the relationship with value in term five while the relationship was cut off in term six for growth index. Just like FUND A, FUND B increased the tracking ability and significance level with values amounting to beta = 1.4877, *p*-value 0.0064 in term three. During term four, these values increased to beta = 2.1807, *p*-value 0.001. The results show that these funds behaved in a very similar way except that FUND A was lagged once to FUND B.

FUNDS C and B, which were found to be bottom performers when the data was collected, also showed valid and significant responses to the value and growth indices. FUND C shared a significant relationship with the value index twice while the relationship with the growth index was shown three times. FUND D was resilient in tracking its own index. The bottom-performing funds proved to be more consistent in replicating their own index than the top two funds, but it is clear that small cap funds had a drift in both value and growth indices. The tracking and drifting pattern was the same; the difference was in timing as some funds became significant a little bit later than other funds in the same group.

4.3.2 Large caps results

Tables 14-17 record the results for large caps. All the funds in the sample of large caps behaved in the same way and proved to not be responsive to the returns of their own index. FUNDS A and B became responsive only once in seven terms while FUNDS C and D responded twice. These results are unexpected since large caps do not appear to be tracking any of the selected local indices. These funds also take the opposite direction to other selected indices as they show a negative beta relationship against their index and many other South African indices. This could strengthen evidence that these funds track other indices not covered in this study.

Table 14: Large cap FUND A; factor model results

LARGECAP		Term 1	Term 2	Term 3	Term 4	Term 5	Term 6	Term 7
		FUND A (LBFT)	FUND A (LBFT)	FUND A (LBFT)	FUND A (LBFT)	FUND A (LBFT)	FUND A (LBFT)	FUND A (LBFT)
	Beta	-0.2923	-0.0600	-0.9409	1.0948	-1.7325	1.2039	1.6066
LARGECAP	**P VALUE**	***0.7527***	***0.9259***	***0.3783***	***0.2903***	***0.1984***	***0.0628***	**0.004**
	Beta	-0.0451	0.0541	-0.0705	-0.1264	-0.4316	0.0585	0.0350
Small cap	p value	0.7618	0.6684	0.5892	0.3711	**0.0218**	0.5617	0.6850
	Beta	0.1246	0.1447	-0.2658	0.0778	0.1048	-0.0126	-0.0295
Resources	p value	0.2419	0.2427	**0.014**	0.5006	0.4115	0.8191	0.4726
	Beta	0.6600	0.443	1.1201	-0.2497	1.3309	-0.2019	-0.1452
Value	p value	0.2324	0.2779	0.0765	0.6727	0.077	0.4211	0.4729
	Beta	0.5326	0.4134	1.3261	-0.1489	1.5576	-0.1131	-0.4419
Growth	p value	0.3006	0.1812	**0.0342**	0.7913	**0.0436**	0.8104	0.2885
	Beta	-0.0659	0.0392	-0.036	0.2058	0.0473	0.0343	0.0268
Industrials	p value	0.5103	0.6944	0.5073	0.0788	0.7262	0.6576	0.7207

Table 15: Large cap FUND B; factor model results

LARGE CAP		Term 1	Term 2	Term 3	Term 4	Term 5	Term 6	Term 7
		FUND B (ABRF)	FUND B (ABRF)	FUND B (ABRF)	FUND B (ABRF)	FUND B (ABRF)	FUND B (ABRF)	FUND B (ABRF)
	Beta	0.4935	0.6115	-0.397	1.2622	-0.9068	2.5989	0.9911
LARGECAP	**P VALUE**	***0.6362***	***0.3294***	***0.7764***	***0.2715***	***0.4771***	**0.0018**	***0.1453***
	Beta	0.124	-0.0352	0.0526	0.0007	-0.3577	0.0762	-0.0127
Small cap	p value	0.4562	0.7729	0.7585	0.9962	**0.0446**	0.5443	0.9061
	Beta	0.0853	-0.2529	-0.2907	-0.0157	0.0632	0.001	0.0434
Resources	p value	0.4594	**0.0373**	**0.0391**	0.9022	0.6020	0.9878	0.3997
	Beta	0.2471	0.0144	0.8279	-0.3541	0.6886	-0.801	-0.0422
Value	p value	0.6890	0.9705	0.3139	0.5890	0.3315	**0.0126**	0.8675
	Beta	0.0170	0.4509	1.0156	-0.1248	1.1489	-1.1106	-0.0655
Growth	p value	0.9763	0.1323	0.2105	0.8414	0.1151	0.0626	0.8997
	Beta	-0.1179	0.0246	-0.1347	0.1551	0.1568	-0.052	0.0278
Industrials	p value	0.2963	0.7982	0.4786	0.2284	0.2257	0.5895	0.7679

Table 16: Large cap FUND C; factor model results

LARGECAP		Term 1	Term 2	Term 3	Term 4	Term 5	Term 6	Term 7
		FUND C (OMSA)	FUND C (OMSA)	FUND C (OMSA)	FUND C (OMSA)	FUND C (OMSA)	FUND C (OMSA)	FUND C (OMSA)
	Beta	0.2394	-0.0445	-2.7823	0.8859	-1.5952	-0.6177	1.4451
LARGECAP	**P VALUE**	***<u>0.8010</u>***	***<u>0.9481</u>***	**0.0391**	***<u>0.3968</u>***	***<u>0.2357</u>***	***<u>0.3990</u>***	**0.0046**
	Beta	0.0477	0.0605	-0.0936	-0.0636	-0.401	0.2336	-0.0235
Small cap	p value	0.7544	0.6510	0.5639	0.6555	**0.0325**	**0.0472**	0.7653
	Beta	0.1745	0.1426	-0.3490	0.0005	0.0857	-0.0052	0.0056
Resources	p value	0.1114	0.2768	**0.0097**	0.9964	0.5013	0.9345	0.8793
	Beta	0.2771	0.3486	2.2628	-0.1008	1.244	0.3586	-0.1652
Value	p value	0.6223	0.4190	**0.0049**	0.8660	0.0975	0.2145	0.3720
	Beta	0.2121	0.453	2.4861	0.0450	1.4591	0.6819	-0.3263
Growth	p value	0.6859	0.1669	**0.0018**	0.9369	0.0581	0.2103	0.3900
	Beta	-0.0842	0.0498	-0.3808	0.1569	0.1306	-0.0370	0.0812
Industrials	p value	0.4117	0.6375	**0.0377**	0.1826	0.3356	0.6767	0.2394

Table 17: Large cap FUND D; factor model results

LARGECAP		Term 1	Term 2	Term 3	Term 4	Term 5	Term 6	Term 7
		FUND D (RMBT)	FUND D (RMBT)	FUND D (RMBT)	FUND D (RMBT)	FUND D (RMBT)	FUND D (RMBT)	FUND D (RMBT)
	Beta	0.8926	-0.2155	1.2718	1.3135	-1.6201	1.4026	1.483
LARGECAP	**P VALUE**	***<u>0.3468</u>***	***<u>0.7450</u>***	***<u>0.2349</u>***	***<u>0.2252</u>***	***<u>0.2611</u>***	**0.0378**	**0.0037**
	Beta	0.0943	0.0088	0.1204	-0.0413	-0.4536	0.0825	0.0118
Small cap	p value	0.5348	0.9458	0.3575	0.7786	**0.0245**	0.4321	0.8805
	Beta	0.1161	0.1646	-0.2261	0.0072	0.0933	-0.0224	0.0095
Resources	p value	0.2838	0.1958	**0.0351**	0.9517	0.4950	0.6971	0.7992
	Beta	0.0181	0.5065	-0.0259	-0.3383	1.2428	-0.2684	-0.1368
Value	p value	0.9742	0.2271	0.9667	0.5839	0.1222	0.3043	0.4589
	Beta	-0.1411	0.4836	-0.0095	-0.2020	1.5025	-0.2552	-0.3715
Growth	p value	0.7867	0.1282	0.9875	0.7311	0.0684	0.6027	0.3283
	Beta	-0.1179	0.0583	-0.0884	0.1857	0.1189	0.0163	0.047
Industrials	p value	0.2496	0.5690	0.5411	0.1276	0.4130	0.8392	0.4942

4.3.3 Industrials results and tables

Tables 18-21 indicate the tracking ability of four sampled industrials mutual funds. This sector is made up of stocks such as construction and materials, electronic and electrical equipment, industrial engineering, industrial transportation, etc. These funds were created with the main objective of replicating these stocks which, in return, constitute the industrial index known as FTSE/JSE J520. They are, therefore, expected to perform well if there is a boom in this sector.

Table 18: Industrials FUND A; factor model results

INDUSTRIALS		**Term 1**	**Term 2**	**Term 3**	**Term 4**	**Term 5**	**Term 6**	**Term 7**
		FUND A (CNCG)	FUND A (CNCG)	FUND A (CNCG)	FUND A (CNCG)	FUND A (CNCG)	FUND A (CNCG)	FUND A (CNCG)
	Beta	0.1180	-0.6358	-2.5859	-0.7258	-1.5762	1.7189	-0.4416
Large cap	p value	**0.0181**	0.3004	**0.0081**	0.4782	0.2103	**0.0081**	0.5356
	Beta	-2.2794	0.2648	0.0503	-0.0409	0.1041	0.2247	-0.0060
Small cap	p value	0.2742	**0.0300**	0.6639	0.7695	0.5445	**0.0271**	0.9580
	Beta	-0.1617	-0.3123	-0.7491	0.4961	-0.3968	-0.2751	-0.1748
Resources	p value	0.1352	**0.0094**	**0.0000**	**0.0001**	**0.0015**	**0.0000**	**0.0021**
	Beta	1.5939	0.7646	2.1333	0.8026	1.4283	-0.4246	0.2881
Value	Significance	**0.0057**	**0.0506**	**0.0003**	0.1741	**0.0432**	0.0894	0.2839
	Beta	1.4231	0.5688	2.3082	1.1057	1.3917	-0.6345	1.0627
Growth	p value	**0.0079**	**0.0540**	**0.0001**	**0.0515**	**0.0532**	0.1758	0.0569
	Beta	0.1330	0.3657	-0.1486	0.1146	0.0061	0.1140	0.0883
INDUSTRIALS	**P VALUE**	***0.1923***	**0.0003**	***0.2495***	***0.3187***	***0.6249***	***0.1392***	***0.3767***

Table 19: Industrials FUND B; factor model results

INDUSTRIALS		Term 1	Term 2	Term 3	Term 4	Term 5	Term 6	Term 7
		FUND B (LIIA)	FUND B (LIIA)	FUND B (LIIA)	FUND B (LIIA)	FUND B (LIIA)	FUND B (LIIA)	FUND B (LIIA)
	Beta	-1.5832	-0.1560	-2.7568	-3.1559	-2.0667	-0.4387	-0.1427
Large cap	p value	**0.0535**	0.7632	**0.0303**	**0.0052**	0.0644	0.5460	0.8413
	Beta	0.0784	-0.0039	-0.3240	-0.1693	-0.3122	0.0323	0.0470
Small cap	p value	0.5447	0.9688	**0.0374**	0.2587	**0.0426**	0.7782	0.6816
	Beta	-0.0692	-0.2383	-0.4618	-0.2534	-0.3448	-0.2863	-0.3024
Resources	p value	0.4526	**0.0186**	**0.0004**	**0.0415**	**0.0017**	**0.0000**	**0.0000**
	Beta	1.0053	0.3900	1.7441	1.9564	1.5253	0.3743	0.2396
Value	Significance	**0.0389**	0.2337	**0.0197**	**0.0027**	0.0150	0.1927	0.3725
	Beta	1.0487	0.3228	2.0945	2.2695	1.7479	1.0202	0.8173
Growth	p value	**0.0215**	0.1924	**0.0049**	**0.0003**	**0.0067**	0.0616	0.1409
	Beta	0.4726	0.6002	0.4091	0.2332	0.2152	0.1319	0.2521
INDUSTRIALS	**P VALUE**	**0.0000**	**0.0000**	**0.0185**	**0.0603**	**0.0569**	***0.1388***	**0.0139**

Table 20: Industrials FUND C; factor model results

INDUSTRIALS		Term 1	Term 2	Term 3	Term 4	Term 5	Term 6	Term 7
		FUND C (RMCF)	FUND C (RMCF)	FUND C (RMCF)	FUND C (RMCF)	FUND C (RMCF)	FUND C (RMCF)	FUND C (RMCF)
	Beta	-2.0718	0.3389	-0.7245	0.0251	-2.1695	-0.1670	0.038
Large cap	p value	**0.0499**	0.6040	0.4339	0.9833	**0.0728**	0.8081	0.9626
	Beta	0.1228	0.3309	0.4422	0.0005	-0.2706	0.1968	0.0971
Small cap	p value	0.4619	**0.0118**	**0.0002**	0.9972	0.1024	0.0748	0.4568
	Beta	-0.3825	-0.2198	-0.463	-0.4389	-0.2541	-0.1805	-0.2668
Resources	p value	**0.0020**	0.0815	**0.0000**	**0.0018**	**0.0284**	**0.0037**	**0.0001**
	Beta	1.5195	-0.1203	0.6792	0.3706	1.5406	0.1658	0.2081
Value	Significance	**0.0161**	0.7694	0.2123	0.5910	**0.0229**	0.5402	0.4951
	Beta	1.6471	0.1158	1.0432	0.5532	1.6663	0.6977	0.7635
Growth	p value	**0.0056**	0.7088	**0.0540**	0.4008	**0.0162**	0.1742	0.2248
	Beta	0.0041	0.3805	-0.0836	0.343	0.2335	0.1389	0.0313
INDUSTRIALS	**P VALUE**	***0.9705***	**0.0004**	***0.5055***	**0.0133**	***0.0564***	***0.1008***	***0.7823***

Table 21: Industrials FUND D; factor model results

INDUSTRIALS		Term 1	Term 2	Term 3	Term 4	Term 5	Term 6	Term 7
		FUND D (GDKI)	FUND D (GDKI)	FUND D (GDKI)	FUND D (GDKI)	FUND D (GDKI)	FUND D (GDKI)	FUND D (GDKI)
	Beta	-1.5592	-0.103	-2.7277	-3.1714	-2.2724	-0.4416	-0.2037
Large cap	p value	0.0633	0.8444	**0.0415**	**0.005**	**0.0508**	0.5655	0.7892
	Beta	0.0775	-0.0068	-0.3353	-0.1678	-0.333	0.0416	0.0403
Small cap	p value	0.5591	0.9465	**0.0408**	0.2625	**0.0377**	0.7287	0.7419
	Beta	-0.0594	-0.238	-0.4865	-0.2675	-0.3434	-0.2861	-0.3137
Resources	p value	0.5289	**0.0204**	**0.0004**	**0.0317**	**0.0025**	**0.0001**	**0.0000**
	Beta	0.9922	0.3425	1.7396	1.9394	1.6462	0.387	0.2596
Value	P value	**0.0464**	0.3021	**0.0269**	**0.0029**	**0.0117**	0.2026	0.3661
	Beta	1.0286	0.2964	2.1017	2.3184	1.8679	1.0153	0.8786
Growth	p value	**0.0275**	0.2376	**0.0072**	**0.0003**	**0.0054**	0.0781	0.1387
	Beta	0.474	0.6162	0.4145	0.2255	0.1928	0.1177	0.246
INDUSTRIALS	**P VALUE**	**0.0000**	**0.0000**	**0.0232**	***<u>0.0688</u>***	***<u>0.0992</u>***	***<u>0.2102</u>***	**0.0241**

The results from the industrials funds show one clear strategy implemented by funds in the selected data sample. All the funds aimed to replicate both value and growth in more or less the same way. FUNDS A and C did not follow the returns of their indices. FUND A became significant to its own index only once while FUND C became significant twice. In term two, FUNDS B, C and D became significant to the industrials' index and abandoned the relationship with both growth and value indices. This broken relationship was re-instated by FUNDS B and D in term three up until term six.

It is evident that the sampled funds within the industrials index behaved in a similar way. Small cap funds shared a similar pattern. The results suggest that the mandate or strategy implemented by industrial funds is to track both value and growth stocks with the same ratio and fully track the industrial index when both value and growth indices experience hard times. Recalling the results obtained in the co-integration test, growth and value stocks were co-integrated during the last term of the study, i.e., the fourth two-year term. This term matches term seven in the style drift results. During this period, all industrials funds moved away from tracking both these indices at the same time. *This sends a message that fund managers do drift from their promised mandate and they do perform stock picking outside their index but they do this with caution and make sure they are consistent with the rules of diversification*. Investing in two co-integrated styles is the same as putting all one's eggs in a single basket. Striking evidence found from the funds in the study sample is that they tend to go in the opposite direction from resource indices. Several significant *p*-values that are associated with negative betas from the resources index were obtained. However, this does not apply only to resource funds. The study found that industrials funds only share positive tracking ability with value and growth indices when these two indices are not co-integrated. Industrials funds shift away from tracking them as soon as they start to be co-integrated. All other indices were found to have a significant negative relationship with industrials funds.

4.3.4 Resources results and tables

The results obtained for the resources funds in Tables 22-25 show that these funds were the most disciplined investments or unit trusts. The top two funds, FUNDS A and B became perfectly responsive to their index from the start to the end. FUND A also shared a significant relationship with both value and growth indices in term three. FUND D tracked the same value and growth indices with high ratios in the same term. During this time, FUND D's returns were not separate and statistically insignificant from the returns of its index. The tracking ratio for FUND D was 3.2113 for value and 2.7104 for growth. This fund was not responsive to returns of the resources index. This was after FUND C had already cut its relationship with the resources index in term two and replicated the value index with a ratio of 4.2873 and 2.5139 for growth. Both tracking ratios were significant.

FUND B became responsive later in term five and the tracking ratio was extremely high, marked at 2.0071 for value and 2.1633 for growth. Both FUNDS C and D fairly replicated their index but made little stock picking along the way. The results are consistent with previously reported negative relationships between industrials and resources.

Tables 22-25 identify the results obtained from the sampled resources mutual funds. These mutual funds track the performance of firms that constitute this index which is known as FTSE/JSE J210. This index is made up of firms that focus on forestry, paper, industrial metals, mining, etc. These funds are expected to reflect the performance of the J210 index.

Table 22: Resources FUND A; factor model results

RESOURCES		Term 1	Term 2	Term 3	Term 4	Term 5	Term 6	Term 7
		FUND A (INVC)	FUND A (INVC)	FUND A (INVC)	FUND A (INVC)	FUND A (INVC)	FUND A (INVC)	FUND A (INVC)
	Beta	-0.3314	-1.2502	-2.9241	1.0677	-1.0129	0.9227	-0.4728
Large cap	p value	0.7635	0.2419	**0.0176**	0.2848	0.4297	0.3237	0.6139
	Beta	0.2227	0.1611	0.0889	0.2427	-0.0848	0.0047	0.0311
Small cap	p value	0.2109	0.4385	0.5456	0.0781	0.6295	0.9744	0.8359
	Beta	0.7247	0.8978	0.6127	0.7111	0.8204	0.6419	0.6828
RESOURCES	**P VALUE**	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**
	Beta	0.4863	0.3868	1.8077	-0.6327	0.2932	-0.2719	0.3488
Value	p value	0.4569	0.5628	**0.0124**	0.2692	0.6796	0.4584	0.3236
	Beta	-0.1357	0.5161	1.8980	-0.4993	0.6565	-0.4277	0.5664
Growth	p value	0.8234	0.3082	**0.0079**	0.3592	0.3666	0.5354	0.4340
	Beta	-0.0243	0.1605	-0.4632	0.0976	0.2377	0.0132	-0.1169
Industrials	p value	0.8377	0.3297	**0.0061**	0.3821	0.0701	0.9066	0.3737

Table 23: Resources FUND B; factor model results

RESOURCES		Term 1	Term 2	Term 3	Term 4	Term 5	Term 6	Term 7
		FUND B (SYMR)	FUND B (SYMR)	FUND B (SYMR)	FUND B (SYMR)	FUND B (SYMR)	FUND B (SYMR)	FUND B (SYMR)
	Beta	-0.7627	-1.1249	-0.0993	0.0544	-3.8497	1.2239	0.5737
Large cap	p value	0.5449	0.1545	0.9396	0.9673	**0.0187**	0.2210	0.5942
	Beta	0.0417	-0.0013	0.109	-0.004	-0.4423	0.1254	0.0102
Small cap	p value	0.8363	0.9932	0.4984	0.9821	**0.0475**	0.4262	0.9525
	Beta	0.827	0.8913	0.3727	0.6699	0.8808	0.7174	0.6503
RESOURCES	**P VALUE**	**0.0000**	**0.0000**	**0.0056**	**0.0000**	**0.0000**	**0.0000**	**0.0000**
	Beta	0.6422	0.7624	0.3609	0.0125	2.0071	-0.3872	0.0196
Value	p value	0.3901	0.1254	0.6388	0.9869	**0.0267**	0.3232	0.9613
	Beta	0.1362	0.3252	0.3675	0.0691	2.1633	-0.7616	-0.2955
Growth	p value	0.8445	0.3831	0.6272	0.9241	**0.0196**	0.2988	0.7217
	Beta	-0.0669	0.0635	-0.1746	0.175	0.1899	-0.018	0.0300
Industrials	p value	0.622	0.5999	0.3290	0.2432	0.2416	0.8815	0.8415

Table 24: Resources FUND C; factor model results

RESOURCES		Term 1	Term 2	Term 3	Term 4	Term 5	Term 6	Term 7
		FUND C (STDG)	FUND C (STDG)	FUND C (STDG)	FUND C (STDG)	FUND C (STDG)	FUND C (STDG)	FUND C (STDG)
	Beta	2.5884	-5.8024	-2.8656	0.2591	9.3737	-7.1161	-4.5916
Large cap	p value	0.4397	**0.0262**	0.2515	0.9203	**0.0204**	**0.0047**	0.1381
	Beta	0.7323	0.0726	0.4043	0.2211	0.4669	-0.2888	0.7795
Small cap	p value	0.0825	0.8636	0.2056	0.5198	0.3815	0.4712	0.0965
	Beta	1.1978	0.633	0.9471	0.3838	0.7459	1.2998	1.0762
RESOURCES	**P VALUE**	**0.0000**	***0.1419***	**0.0006**	***0.2515***	**0.0300**	**0.0000**	**0.0000**
	Beta	-0.8077	4.2873	0.5291	-0.5594	-5.6732	2.0675	1.5814
Value	p value	0.6402	**0.0172**	0.7133	0.7101	**0.013**	0.0533	0.1617
	Beta	-2.9014	2.5139	1.7691	0.2975	-5.4411	5.1124	3.1982
Growth	p value	0.1578	**0.0448**	0.2065	0.8308	**0.0209**	**0.0047**	0.1848
	Beta	-0.1626	-1.303	-0.313	-0.063	0.6057	-0.2432	-0.9761
Industrials	p value	0.4986	**0.0028**	0.3334	0.8348	0.1359	0.4058	**0.0283**

Table 25: Resources FUND D; factor model results

RESOURCES		Term 1	Term 2	Term 3	Term 4	Term 5	Term 6	Term 7
		FUND D OMTM)	FUND D OMTM)	FUND D OMTM)	FUND D OMTM)	FUND D OMTM)	FUND D OMTM)	FUND D OMTM)
	Beta	-0.4346	0.6496	-4.0618	0.3562	-3.853	0.0649	-0.315
Large cap	p value	0.7319	0.4869	**0.0290**	0.8164	**0.0352**	0.9560	0.8185
	Beta	0.0205	0.4118	-0.1068	0.128	-0.3899	0.1616	0.2420
Small cap	p value	0.9194	**0.0271**	0.6321	0.5423	0.1172	0.3882	0.2752
	Beta	0.6882	0.828	0.0937	0.5756	0.9897	0.928	0.662
RESOURCES	**P VALUE**	**0.0000**	**0.0000**	***0.6023***	**0.0014**	**0.0000**	**0.0000**	**0.0000**
	Beta	0.5661	-0.8113	3.2113	-0.2251	1.6379	-0.1194	0.3144
Value	p value	0.4519	0.1700	**0.0038**	0.7980	0.1036	0.7967	0.5428
	Beta	0.1328	-0.3569	2.7104	0.0395	2.3201	-0.0836	0.329
growth	p value	0.8495	0.4214	**0.0121**	0.9623	**0.0255**	0.9236	0.7561
	Beta	-0.0914	0.3121	-0.4862	-0.0026	0.1967	0.0075	-0.1251
Industrials	p value	0.5044	**0.0338**	**0.0531**	0.9877	0.2798	0.9580	0.5153

4.3.5 Growth results and tables

Table 26: Growth FUND A; factor model results

GROWTH		Term 1	Term 2	Term 3	Term 4	Term 5	Term 6	Term 7
		FUND A (FEQF)	FUND A (FEQF)	FUND A (FEQF)	FUND A (FEQF)	FUND A (FEQF)	FUND A (FEQF)	FUND A (FEQF)
	Beta	-1.1465	-1.1657	-3.3096	-2.0048	-2.6009	0.0168	-1.4201
Largecap	p value	0.0945	**0.031**	**0.0023**	**0.0373**	**0.0306**	0.9795	**0.0281**
	Beta	0.1068	0.1885	-0.0093	-0.0337	-0.1539	0.1772	-0.0738
Small cap	p value	0.3273	0.0722	0.9414	0.7934	0.3430	0.0927	0.4681
	Beta	-0.0542	0.0975	-0.5725	0.0411	0.1203	-0.0849	-0.0539
Resources	p value	0.4833	0.3353	**0.0000**	0.6968	0.2853	0.1409	0.2660
	Beta	1.041	0.9261	2.6894	1.3761	1.6004	0.167	0.8348
Value	p value	**0.0117**	**0.0071**	**0.0000**	**0.0134**	**0.017**	0.5184	**0.0009**
	Beta	0.8736	0.6447	2.451	1.3223	1.7869	0.5509	1.5606
GROWTH	**P VALUE**	**0.0225**	**0.0126**	**0.0001**	**0.0127**	**0.0094**	***0.2601***	**0.0022**
	Beta	0.0538	0.331	-0.0539	0.2269	0.1825	0.1046	0.0557
Industrials	p value	0.4614	**0.0002**	0.7027	0.0355	0.1289	0.1940	0.5292

Table 27: Growth FUND B; factor model results

GROWTH		Term 1	Term 2	Term 3	Term 4	Term 5	Term 6	Term 7
		FUND B (STCA1)	FUND B (STCA1)	FUND B (STCA1)	FUND B (STCA1)	FUND B (STCA1)	FUND B (STCA1)	FUND B (STCA1)
	Beta	0.5939	-0.9869	0.2876	0.571	-1.6707	1.6725	0.5359
Large cap	p value	0.5304	0.1374	0.8642	0.5908	0.2132	**0.0337**	0.4387
	Beta	0.4436	0.1382	-0.0211	-0.0725	-0.0834	0.1244	0.0357
Small cap	p value	**0.0048**	0.2844	0.9181	0.6176	0.6489	0.3105	0.7471
	Beta	-0.3411	-0.2497	-0.3475	-0.0528	0.0376	-0.0188	0.041
Resources	p value	**0.0024**	**0.0504**	**0.0403**	0.6566	0.7670	0.7792	0.4371
	Beta	0.4090	1.1426	0.4711	0.1217	1.2670	-0.2600	0.1969
Value	p value	0.4658	**0.0075**	0.6326	0.8414	0.0908	0.3924	0.4488
	Beta	-0.0196	0.8569	0.234	-0.0342	1.2852	-0.7104	0.0896
GROWTH	**P VALUE**	***0.9699***	**0.0079**	***0.8092***	***0.9529***	***0.0928***	***0.2165***	***0.8663***
	Beta	-0.0039	0.115	0.2125	0.2667	0.0991	-0.0255	0.0274
Industrials	p value	0.9689	0.2601	0.3540	**0.0283**	0.4626	0.7854	0.7765

Table 28: Growth FUND C; factor model results

GROWTH		Term 1	Term 2	Term 3	Term 4	Term 5	Term 6	Term 7
		FUND C (FGGA)	FUND C (FGGA)	FUND C (FGGA)	FUND C (FGGA)	FUND C (FGGA)	FUND C (FGGA)	FUND C (FGGA)
	Beta	-0.6099	-0.0496	-5.004	1.183	-1.7515	-0.4341	-0.2184
Large cap	p value	0.4922	0.9253	**0.0003**	0.2159	0.1080	0.6414	0.7582
	Beta	0.0792	0.0791	-0.0486	0.0442	0.0159	0.1931	0.1467
Small cap	p value	0.5781	0.4464	0.7619	0.7331	0.9140	0.1937	0.2015
	Beta	-0.1339	0.1610	-0.5582	-0.1333	0.0878	0.1453	-0.0233
Resources	p value	0.1889	0.1153	**0.0001**	0.2127	0.3933	0.0769	0.6665
	Beta	1.1066	0.3432	3.3686	-0.2226	1.1971	0.2975	0.2914
Value	p value	**0.0387**	0.3056	**0.0000**	0.6827	**0.0490**	0.4176	0.2768
	Beta	0.5728	0.0644	3.9457	-0.1524	1.3498	0.6426	0.6965
GROWTH	**P VALUE**	***0.2445***	***0.7979***	**0.0000**	***0.7689***	**0.0304**	***0.3531***	***0.2064***
	Beta	0.0185	0.3899	-0.5810	0.2330	0.1554	0.0482	0.0217
Industrials	p value	0.8457	**0.0000**	**0.0018**	0.0321	0.1568	0.6705	0.8265

Table 29: Growth FUND D; factor model results

GROWTH		Term 1	Term 2	Term 3	Term 4	Term 5	Term 6	Term 7
		FUND D (SYGA)	FUND D (SYGA)	FUND D (SYGA)	FUND D (SYGA)	FUND D (SYGA)	FUND D (SYGA)	FUND D (SYGA)
	Beta	0.0045	0.7728	1.0805	0.5848	-1.1281	0.6846	-0.772
Large cap	p value	0.9948	0.1503	0.2580	0.5736	0.3538	0.3150	0.2412
	Beta	0.2006	0.3720	0.3426	0.1907	-0.0097	0.2256	-0.0065
Small cap	p value	0.0804	**0.0007**	**0.0046**	0.1826	0.9535	**0.0394**	0.9507
	Beta	-0.1139	-0.1832	-0.3024	-0.0497	0.0181	0.0717	-0.0092
Resources	p value	0.1604	0.0752	**0.0021**	0.6690	0.8750	0.2271	0.8525
	Beta	0.4090	-0.0030	1.12E	-0.1505	0.8563	-0.0100	0.4773
Value	p value	0.3290	0.9928	1.0000	0.8003	0.2061	0.9699	0.0564
	Beta	0.2387	-0.0187	-0.2761	-0.0145	0.8537	-0.269	1.0052
GROWTH	**P VALUE**	***0.5401***	***0.9409***	***0.6143***	***0.9796***	***0.2168***	***0.5924***	**0.0505**
	Beta	0.0451	0.0918	0.1188	0.1178	0.1125	-0.1122	0.0009
Industrials	p value	0.5532	0.2666	0.3587	0.3132	0.3597	0.1773	0.9199

From the sample of growth funds used, no pattern can be identified. Of the sample, with two top performers and two bottom performers, FUND A stands out as the only fund that fairly responded to other JSE indices, while other funds behaved like large caps funds. FUND A invested in both growth and value stocks as it tracked returns of both these indices. More interesting, during term six, Fund A's returns were insignificant to both value and growth indices. FUND B started off by sharing a significant relationship with value stocks for the first two terms and, thereafter, this relationship faded away. The same is true for FUND C whose returns were significant in the value index three times in seven terms. On the other hand, FUND C had a significant relationship with small cap three times in seven terms. Thus, it can be concluded that growth stocks share a visible relationship with the value index. In most cases, when growth funds were responsive to the growth index, they were also responsive to the value index. Whenever they negatively tracked their own index (growth), they also negatively tracked value index. These two indices shared a near perfect linear relationship.

4.3.6 Value results and tables

Turning to the value stocks style, a style that has apparently been tracked by many styles, interesting results were found. The sampled funds were fairly responsive to the returns of their own index, with FUNDS A and D being significant five and four times, respectively. However, the results shown in Tables 30-33 show a clear trend of style drift that took place during the fifth to seventh terms.

Interesting findings were obtained when matching these results with those from the Engle-Granger two-step procedure. This co-integration test revealed that the two indices, i.e., value and resources were not co-integrated in the first two years of the period under study. Although three funds in the study sample, i.e., FUNDS A, C and D, were not tracking the returns of the resources index, FUND B was statistically significant. This was a safe move for FUND B because there was no long-run relationship at that time. The results from Engle-Granger show that during the second two years of this analysis, which can be equated to term three in the factor model, these two funds started to be co-integrated. During this period, all the funds shifted away from tracking the index; the results showed that most betas were negative and significant, and where positive betas were recorded, the *p*-values pronounced them to be statistically insignificant.

During the fourth second year of the Engle-Granger two-step model, the results show that these two indices were not co-integrated. When these results were compared to those from the asset class factor model, it was found that three funds in the sample started to build a positive relationship with the resource index. Therefore, acknowledgement of market timing skills and diversification hunger among fund managers is important in this instance.

Table 30: Value FUND A; factor model results

VALUE		Term 1	Term 2	Term 3	Term 4	Term 5	Term 6	Term 7
		FUND A (INVF)	FUND A (INVF)	FUND A (INVF)	FUND A (INVF)	FUND A (INVF)	FUND A (INVF)	FUND A (INVF)
	Beta	-1.6687	0.2741	-3.5324	0.1048	3.2563	-2.2535	-7.2575
Large cap	p value	**0.0156**	0.7113	**0.0014**	0.9271	**0.0497**	0.1098	**0.0001**
	Beta	0.0523	0.5854	0.2092	-0.0716	0.7523	-0.0351	0.2546
Small cap	p value	0.6273	**0.0002**	0.1087	0.6479	**0.0014**	0.8733	0.3427
	Beta	-0.4753	-0.3204	-0.7131	0.0900	0.2633	0.5466	0.6013
Resources	p value	**0.0000**	**0.0265**	**0.0000**	0.4839	0.0939	**0.0000**	**0.0000**
	Beta	1.9539	0.3351	3.0614	0.2821	-1.9441	0.9192	2.3679
VALUE	**P VALUE**	**0.0000**	***0.4726***	**0.0000**	***0.6681***	**0.0352**	***0.0972***	**0.0004**
	Beta	1.2754	0.0496	2.7342	0.0574	-1.7081	1.8062	5.4447
Growth	p value	**0.0011**	0.8877	**0.0000**	0.9269	0.0685	0.0839	**0.0001**
	Beta	-0.0827	0.4152	-0.4057	0.0914	0.1950	-0.2637	-0.6664
Industrials	p value	0.2558	**0.0006**	**0.0061**	0.4777	0.2393	0.1234	**0.0057**

Table 31: Value FUND B; factor model results

VALUE		Term 1	Term 2	Term 3	Term 4	Term 5	Term 6	Term 7
		FUND B (FIEU)	FUND B (FIEU)	FUND B (FIEU)	FUND B (FIEU)	FUND B (FIEU)	FUND B (FIEU)	FUND B (FIEU)
	Beta	-0.9888	-1.9023	-0.7042	0.2876	-0.3575	0.1833	-1.3237
Large cap	p value	0.2239	**0.0075**	0.5686	0.7830	0.7728	0.8172	0.1760
	Beta	0.074	0.0540	0.2834	0.2751	-0.0801	0.0953	0.169
Small cap	p value	0.5682	0.6875	0.0650	0.0581	0.6379	0.4488	0.2808
	Beta	0.3436	0.3155	-0.0678	0.1541	0.2917	0.3811	0.3358
Resources	p value	**0.0040**	**0.0189**	0.5784	0.1906	**0.0160**	**0.0000**	**0.0000**
	Beta	0.9147	1.2387	0.5415	0.0492	0.2821	-0.1429	0.5767
VALUE	**P VALUE**	***0.0598***	**0.0057**	***0.4546***	***0.9344***	***0.6815***	***0.6468***	***0.1177***
	Beta	0.4187	0.9575	0.7764	-0.2193	0.1598	0.1085	1.1226
Growth	p value	0.3295	**0.0047**	0.2774	0.7007	0.8197	0.8533	0.1374
	Beta	-0.0964	0.056	-0.0214	0.1533	0.2819	0.0648	-0.1339
Industrials	p value	0.2704	0.5979	0.8979	0.1935	**0.0276**	0.5020	0.3258

Table 32: Value FUND C; factor model results

VALUE		Term 1	Term 2	Term 3	Term 4	Term 5	Term 6	Term 7
		FUND C (AHMF)	FUND C (AHMF)	FUND C (AHMF)	FUND C (AHMF)	FUND C (AHMF)	FUND C (AHMF)	FUND C (AHMF)
	Beta	-0.2103	0.7633	-1.0548	2.4206	-3.2195	-0.3382	-1.9632
Large cap	p value	0.8225	0.2382	0.3813	**0.0395**	**0.0254**	0.6899	0.0983
	Beta	0.4431	0.5511	0.2887	0.2671	-0.2007	0.1696	-0.013
Small cap	p value	**0.0046**	**0.0001**	**0.0538**	0.0944	0.3015	0.2093	0.9447
	Beta	-0.3106	-0.0206	-0.4767	-0.0274	0.3293	0.2034	0.3542
Resources	p value	**0.0051**	0.8660	**0.0002**	0.8318	**0.0167**	**0.0076**	**0.0002**
	Beta	0.4048	-0.1773	1.3752	-0.9089	2.0659	0.2865	0.9875
VALUE	**P VALUE**	***0.4669***	***0.6612***	**0.0545**	***0.1728***	**0.0103**	***0.3909***	**0.0284**
	Beta	0.6979	-0.2687	1.2826	-1.1577	1.8984	0.6141	1.6971
Growth	p value	0.1811	0.3805	0.0680	0.0702	**0.0202**	0.3295	0.0684
	Beta	0.1186	0.3138	-0.071	0.3298	0.1233	0.0734	-0.1945
Industrials	p value	0.2432	**0.0025**	0.6635	**0.0131**	0.3875	0.4771	0.2387

Table 33: Value FUND D; factor model results

VALUE		Term 1	Term 2	Term 3	Term 4	Term 5	Term 6	Term 7
		FUND D (HLMK)	FUND D (HLMK)	FUND D (HLMK)	FUND D (HLMK)	FUND D (HLMK)	FUND D (HLMK)	FUND D (HLMK)
	Beta	-1.1547	-0.2157	-1.6745	-2.8275	-1.9715	-0.1719	-0.2400
Large cap	p value	0.2203	0.7586	**0.0340**	**0.0077**	0.1290	0.8122	0.7825
	Beta	0.0537	0.2320	0.0052	-0.4309	-0.1269	0.1814	0.0493
Small cap	p value	0.7205	0.0948	0.9558	**0.0032**	0.4730	0.1174	0.7240
	Beta	-0.3783	-0.3492	-0.4259	-0.2848	-0.2764	-0.2675	-0.2945
Resources	p value	**0.0008**	**0.0113**	**0.0000**	**0.0157**	**0.0272**	**0.0001**	**0.0000**
	Beta	1.1734	0.5118	1.4504	1.9829	1.6565	0.4258	0.7737
VALUE	**P VALUE**	**0.0379**	***0.2488***	**0.0022**	**0.0013**	**0.0233**	***0.1382***	**0.0209**
	Beta	0.9248	0.3967	1.3256	2.0219	1.5269	0.5715	0.5156
Growth	p value	0.0776	0.2368	**0.0042**	**0.0006**	**0.0397**	0.2884	0.4430
	Beta	0.1528	0.2375	0.0335	0.2037	0.0552	0.1733	0.3013
Industrials	p value	0.1334	**0.0320**	0.7495	0.0805	0.6706	**0.0529**	**0.0159**

Tables 10-33 presented the values of betas (β) and R-squared for the sample of 24 South African mutual funds. As stated in the section on methodology, betas are used to check the relationship between mutual funds and indices. Each fund was regressed with all six indices per term and all betas were recorded. This was done for all seven terms and all 24 mutual funds. This resulted in a total number of 168 regressions.

4.3.7 R-Squared results and tables

Tables 34-39 provide R-squared for linear regression models run for the style drift objective. Large cap funds produced quite different results from other funds; however R-squared values prove that the regression model was used properly and was sufficient to capture the relationship between dependent and explanatory variables. By definition R-squared is a broad indication of the fit of the model to the data.

Table 34: Small caps R-squared

Small cap	Term 1	Term 2	Term 3	Term 4	Term 5	Term 6	Term 7
FUND A	0.7717	0.6721	0.7651	0.7106	0.8116	0.8450	0.8438
FUND B	0.7617	0.5066	0.7484	0.7851	0.7844	0.8596	0.7501
FUND C	0.4656	0.5566	0.7648	0.5535	0.4262	0.7881	0.7126
FUND D	0.6621	0.5000	0.6364	0.5918	0.6657	0.7597	0.6776

Table 35: Large caps R-squared

Large cap	Term 1	Term 2	Term 3	Term 4	Term 5	Term 6	Term 7
FUND A	0.9553	0.8505	0.8968	0.9111	0.9028	0.9571	0.8902
FUND B	0.9198	0.8505	0.8915	0.8953	0.8343	0.9373	0.8369
FUND C	0.9621	0.9005	0.8991	0.9119	0.8586	0.9514	0.8779
FUND D	0.9628	0.8924	0.8865	0.9089	0.9057	0.9546	0.8796

Table 36: Industrials R-squared

Industrials	Term 1	Term 2	Term 3	Term 4	Term 5	Term 6	Term 7
FUND A	0.8445	0.7876	0.8260	0.8327	0.6657	0.7597	0.7535
FUND B	0.8589	0.7830	0.8572	0.8358	0.7510	0.9328	0.8486
FUND C	0.8173	0.7614	0.8204	0.8101	0.7835	0.8369	0.6877
FUND D	0.8421	0.7599	0.8460	0.8363	0.9368	0.9307	0.8433

Table 37: Resources R-squared

Resources	Term 1	Term 2	Term 3	Term 4	Term 5	Term 6	Term 7
FUND A	0.9150	0.8921	0.9187	0.9382	0.9036	0.9047	0.8823
FUND B	0.8844	0.8854	0.8882	0.8922	0.8701	0.9542	0.8589
FUND C	0.6199	0.5148	0.4645	0.4858	0.6961	0.5383	0.6568
FUND D	0.8160	0.8621	0.8642	0.8397	0.8259	0.9339	0.8631

Table 38: Growth R-squared

Growth	Term 1	Term 2	Term 3	Term 4	Term 5	Term 6	Term 7
FUND A	0.8853	0.8190	0.8754	0.8780	0.8859	0.9395	0.8863
FUND B	0.8957	0.8006	0.8456	0.8605	0.6724	0.8999	0.8407
FUND C	0.8568	0.6877	0.9058	0.9146	0.8181	0.9535	0.8840
FUND D	0.8208	0.6928	0.7712	0.7793	0.8588	0.9400	0.8473

Table 39: Value R-squared

Value	Term 1	Term 2	Term 3	Term 4	Term 5	Term 6	Term 7
FUND A	0.5535	0.6366	0.7002	0.7424	0.8943	0.8969	0.9261
FUND B	0.7388	0.8156	0.7878	0.7507	0.6971	0.881	0.8585
FUND C	0.7500	0.7970	0.8587	0.8547	0.8756	0.9180	0.8209
FUND D	0.8543	0.7811	0.8101	0.8294	0.8408	0.7952	0.7520

Since R-squared values are high for large caps, there are no concerns that the model used was ambiguous. It can thus be concluded that the model captured and reported the exact relationship between large cap funds and sectorial indices. Small cap R-squared values were also high with the exception of FUND C which consistently reported low values which are further evidence of low displaying or demonstrating power. This was the case for FUND C of resources. Industrials, growth and value R-squared values were also high. Overall, looking at the numbers from the R-squared tables, it can be concluded that the model used to evaluate the relationships between funds and indices was efficient and correctly implemented. The regression outputs can thus be interpreted with confidence.

4.4 Chapter summary

The three models discussed in Chapter 3 were run and the results were presented in this chapter. Three different tests were conducted with the first model i.e., the ADF test, being the foundation of Engle-Granger two-step approach. The ADF test was not mentioned as an independent model simply because it is compulsory when modelling price data. The ADF results enabled the researcher to progress to the Engle-Granger co-integration test which was, in turn, successfully conducted. The results of this test were tabulated in Table 8 for the period of eight years which was broken down into four equal cycles and one large period consisting of the full eight years. The second method, the asset factor model, was also executed and its results were tabulated in Tables 10 to 39.

CHAPTER 5: CONCLUSIONS AND RECOMMENDATIONS

5.1 Introduction

Having discussed the study's findings in the previous chapter, this chapter provides answers to the questions posed in Chapter 1 as well as conclusions drawn from the results and interpretations set out in Chapter 4. This chapter also combines the results obtained from the two different methods used and ultimately compares them with the results obtained by both local and international scholars. By so doing, the study highlights the similar and contradictory findings of other scholars. Furthermore, by comparing the results, the gaps in the literature are revealed. Finally, recommendations are provided for further research and the limitations encountered during the course of the study are discussed.

5.2 Discussions and conclusions

This study critically analysed style investing from a South African perspective. Six South African indices and a sample of four mutual funds per index were used to search for style drift and long-run relationships. Of the four mutual funds for each index, the first two were index top achievers at the time the data was collected, and the last two were bottom achievers. To achieve the study's two objectives, two different methodologies were used, i.e., the Engle-Granger two-step model for long-run relationship and the asset class factor model for style drift. Data was collected for a period of eight years, from 2006 to 2014 and both daily and weekly data were used. The resultant number of weekly observations amounted to 427 and 2 019 daily observations were recorded.

5.2.1 Relationship between indices

Objective number 1: "to analyse the long-run relationship between six different South African indices (i.e., value, growth, small caps, large caps, industrials and resources)".

Tests for co-integration were conducted because stock picking and herding behaviour has previously been reported in the South African mutual funds/money management industry (Gilmour and Smit, 2002). One of the biggest problems about stock picking is that it deters diversification if the long-run relationship is not known. Therefore, to tackle this issue, the long-run relationship must be investigated and acknowledged with certainty. This study was motivated by the fact that no studies have been published that shed light on stock picking against diversification or long-run relationships.

Using the co-integration methodology, the results show that the long-run relationship can be better understood if the tests are conducted using two-year data and above. The results revealed that crucial co-integrating relationships were not reported by the overall model which covered the whole eight-year period. By breaking the data into many different terms, the study was successful in indicating how the indices were related prior to recession, during recession and post-recession. In addition, the roll-over strategy was implemented to increase the number of observations and to track continuous relationships between the six selected indices.

The results from the segregated periods show that during the global financial crisis, **nine** indices were co-integrated since they behaved in the same way and had a long-run relationship. This was no surprise because all the indices used in this study are from the same economy and probably share the same investors. They therefore suffer the same external and internal shocks, with recession being one of the biggest external shocks. In this period, of 15 possible co-integrating equations from six indices, **nine** were reported co-integrated while **six** remained resilient and non-co-integrated. These findings are in line with Anderson et al. (2009) who investigated co-integration relationships between five international markets and found that, of 10 possible relationships, five were co-integrated

Soon after the recession, these indices repelled each other and reduced the number of co-integrating equations to **six** and further down to **two** in the last two years of the period covered in this study. This is testimony to the susceptibility of the South African mutual fund industry to change within a short period of time.

Throughout the operation, the study recorded a repeated and significant long-run relationship between the following three pairs, when the segregated period method was implemented. It was also demonstrated that the relationship between these pairs was strong for the roll-over methodology.

- small caps and industrials;
- small caps and large caps; and
- small caps and growth.

This long-run relationship was further confirmed by the bivariate model which covered a period of eight years. The study found a significant long-run relationship between these indices and thus recommends maximum diversification through investing in any of the available non-co-integrated indices but avoidance of investing in any of the co-integrated indices at the same time. Investors are, therefore, advised to look at the long-run relationship between the indices they wish to invest in. While they may be co-integrated, there may still be deviations in the short-run before market forces drive the market back to equilibrium. The long-run relationship between these three pairs was also confirmed by the results from the roll-over methodology. Small caps and industrials shared a long-run relationship throughout the study period. Since this pair was found to share a long run relationship using both the segregated period and roll-over methodologies, it can therefore be concluded that these two pairs trend together in the long run. Notably, *p*-values of (small cap/large cap) and (small cap/growth) were rapidly reduced until they become significant at the eight-year period, symbolising a long-run relationship.

5.2.2 Causes and the duration of style drift

Objective number 2: "to investigate and analyse the presence, causes and duration of style drift in the sampled funds that constitute the six South African indices investigated in objective one".

The Sharpe (1992) asset class factor model was used to investigate and analyse the presence, causes and duration of style drift of South African unit trusts. In the most recent literature, Wermers (2010) puts forward possible reasons for style drift. These range from unintentional drift, when stock changes its characteristics over time, to intentional drift, and when investors are faced with pressure from peers. Breaking the data into seven terms revealed that unit trusts keep changing their investment strategies. In the period covered in this study, two apparent style drift trends and abundant stock picking behaviour were revealed. Resources mutual funds proved to be the most disciplined and transparent means of investment. They stuck to the promised mandate which is usually provided by the name of the unit trust or fund. The regression model used for this objective proved to be efficient since the number of necessary observations was met, R-squared values were high and most of the results were significant.

Most mutual funds do track the indices that they are supposed to track but they also engage in active trading which drives them to invest in a certain index for a shorter period of time and soon move to invest in another. The findings of this study relate to those of Moore (2013) who also used the asset class factor model to quantify funds misspecification in South African financial markets. Moore (2013) reported that very few managers follow one investment style but follow another in order to frame investor returns expectations. Furthermore, the returns of a large portion of funds differ from the returns of purported style.

Large cap unit trusts were found not to follow their index and other indices in this study. Hence, these funds either invest in other South African indices that are not covered in this study or they invest in different asset classes like bonds, money market or a combination of asset classes not covered in this study. Furthermore, the study found that mutual funds or fund managers were highly influenced by herding behaviour. There is insufficient evidence to show that managers do not attempt to control for style drift. As long as their peers (funds with the same investment mandate) are still investing in that index, they stay and suddenly break the relationship at the same time. South Africa fund managers seem to confirm Wermers' (2012) findings that controlling for style drift does not necessarily result in improved performance and superior returns.

Fund managers seem to deviate from drifting when there is co-integration between their own index and the index they drifted to. This is concrete evidence of accurate market timing on the part of these managers. Consequently, they are regarded as perfect market timers. This is in line with Gilmour and Smit (2002) study on herding in the South African unit trust industry. Gilmour and Smit (2002) documented that levels of herding increased from 2, 2% in the first 10 quarters of the period covered by their study to 2,7% in the last 10 quarters of the period. Despite the increase in herding during the period of study, they also show that, from 1996 to 1997 when there was high volatility in the market, the trend of herding disappeared. This is testimony to how fund managers time their strategies.

Combining the results of both the models used in this study shows that funds exercise active trading in the form of stock picking and style drift. Furthermore, the study found that fund managers have perfect market timing. When they drift, they shift to the opposite direction of co-integration, which is seen as safe and efficient. While this study presents results from two distinct methodologies, it cannot confirm that fund managers examine co-integration relationships before making their move. The study therefore refrains from using "look ahead bias”, or assuming that managers know that particular indices would have moved closer together in one period compared to another. It was, therefore, surprisingly to find that unit trusts keep changing their investment strategies as the co-integration between indices kept changing. The study fell short, however, of investigating the lead-lag relationship between indices and mutual funds. Simply put, it did not attempt to determine if style drift and stock picking initiate changes in long-run relationships or whether changes in long run-relationships cause funds to change their investment strategies. More importantly, the results showed a near-perfect linear relationship between value and growth stock, meeting prior expectations. The literature documents them as the opposite of each other with regard to returns; Barberis and Shleifer (2003) stated that when there is a boom growth is expected to experience drought and vice versa for value. However, this was not the case in this study.

Furthermore, the study found a negative relationship between industrials and resources. In terms of returns, these two indices follow the concept of style and twin. Due to the fact that this concept is not based solely on returns dynamics, it is inappropriate to call industrials and resources “style and twin”; neither can it be postulated that value and growth are not style and twin. To be able to do this, there is a need to go the extra mile to examine changes and relationships in market capitalisation. This study laid a solid foundation to shed light on the concept of style and twin. Should market capitalisation of growth and value be positively related, and that of resources and industrials be negatively related, then sufficient proof to make a ruling on them would have been gathered.

5.3 Recommendations

This study examined style investing from the dimensions of asset allocation and diversification which were obtained by comparing asset allocation against co-integration results. As discussed in the conclusions above, the study found style drift to move in the opposite direction of co-integration and such drift is regarded as safe from a portfolio manager’s point of view. Turning to recommendations for further studies, it would be useful to gain deeper insight into style investing in terms of returns and consistency and unit trusts. Gilmour and Smit (2002) documented herding trading in the money management industry, and this study documented a few style drifts and drastic changes in co-integrating relationships. However, returns and performance consistency overtime in this industry have received little attention. Teo and Woo (2001) also documented perfect market timing by fund managers. However, Teo and Woo (2001) indicated that the relationship between style consistency and fund performance remains unclear. Combining the findings on herding in this industry and style drift, it would be interesting to examine if higher returns are obtained from such conduct in the future.

5.4 Limitations of the study

Numerous limitations materialized during the course of this study. These took the form of data and models. These limitations are therefore disclosed since they affect how the results are interpreted in the drive to reach conclusions.

This study analysed style investing for a period of eight years due to the short life span of mutual funds in South Africa. While the data for indices were largely available, the aim was to test the reaction of unit trusts to selected indices in equal or comparable time horizons. Therefore, the researcher opted to conduct the study for an eight-year period. Furthermore, two different and unrelated models, i.e., co-integration methodology and the factor model were used. These models have different data frequency requirements, with the factor model giving efficient, accurate and optimal results when weekly data were used and taking 61 observations per regression. This was provided by Sharpe (1992) in the paper titled "Asset allocation: management style and performance measurement". Sharpe popularised the factor model.

On the other hand, the Engle-Granger two-step procedure required daily data to be used when dealing with financial data, more especially when modelling returns co-integration. Sjö (2008) confirmed that in order to obtain relevant results from bivariate co-integration methodology, daily data must be used and the observations must amount to more than 400.

This study aimed to evaluate style drift and the long-run relationship over time rather than at a single point in time. In order to do so, the data needed to be divided into different terms. It was difficult to keep abandoning past observations because of the observation requirement. Weekly data was, therefore, collected for the asset class factor model and daily data for the Engle-Granger two-step procedure. This led to accurate results in both models but it also rendered the results very difficult to match on a one-on-one basis. Although they can be equated, the study still found that some terms in the asset class factor model had observations that stretched to two different terms in the co-integration results.

The biggest limitation is that this study implemented two different, un-related concepts i.e., style drift and co-integration. As this is a unique study, its results are not directly comparable to any findings that can be found in the existing literature.

5.5 Concluding remarks

Gilmour and Smit (2002) found that the South African money management industry is characterized by herding and stock picking. This study examined the relationship between six selected South African indices in relation to the tracking ability of the funds which constitute these indices in order to determine if the concept of diversification was executed. Two methodologies were used: the (Engle and Granger (1987)) two-step procedure and the Sharpe (1992) asset class factor model. The study covered a period of eight years, with both daily and weekly data collected and used.

Bearing in mind the limitations disclosed in the previous section, the study documents the following results:

- South African indices are susceptible to drastic changes in a short period of time, i.e., as little as two years. Relationships between these indices keep changing over time. The study found that as time goes on, relationships between indices are established, abandoned and possibly resurrected over a period of eight years.

- among the six local indices investigated, the study found two instances of apparent style drift (industrials to resources and value stocks to resources) and abundant stock picking behaviour. However, stock picking was in the opposite direction to co-integration, which suggests a maximised level of diversification and perfect market timing by fund managers. Furthermore, fund managers do not seem to be controlling style drift. All funds show similar trends compared to their peers in the market which may possibly illustrate herding behaviour, which is behaviour that mimics peers' movements.

- from a South African perspective, value and growth funds did not show that they are style and twins. The literature pronounces them the opposite of each other. However, in South Africa, they appear to perfectly complement each other. Only industrials and resources showed the characteristics of being fund and twin. The evidence for this proposition can be extracted from both the short-run and long-run relationship results. Small caps and industrials proved to have a strong long-run relationship, followed by (small cap/growth) and (small cap/ value). In the short run, the resources index moved in the opposite direction from all the other five indices.

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7. APPENDICES

7.1 Appendix A: List and full names of unit trusts used

LARGE CAP

1. Stanlib alsi 40 fund class A (LBFT) FUND A
2. Absa large cap fund (ABRF) FUND B
3. Oldmutual top 40 fund A (OMSA) FUND C
4. Momentum top 40 index fund (RMBT) FUND D

SMALLCAP

1. Nedgroup investment entrepreneur fund R (NDBE) FUND A
2. Oldmutual small companies Fund R (OMSC) FUND B
3. Stanlib small cap fund class A (GDSC) FUND C
4. Coronation smaller companies fund (COSG) FUND D

RESOURCES

1. Investec commodity fund class R (INVC) FUND A
2. Nedgroup investment mining and resources fund class R (SYMR) FUND B
3. Stanlib gold and precious metal fund class R (STDG) FUND C
4. Oldmutual mining and resources Fund R (OMTM) FUND D

VALUE

1. Investec value fund class R (INVF) FUND A
2. Element Islamic equity fund A (FIEU) FUND B
3. Cadiz mastermind fund class A (AHMF) FUND C
4. Marriott dividend growth fund class R (HLMK) FUND D

GROWTH

1. Foord equity fund (FEQF) FUND A
2. Sim top choice equity fund A (STCA1) FUND B
3. Investec growth fund class A (FGGA) FUND C
4. Nedgroup investment growth fund A (SYGA) FUND D

INDUSTRIALS

1. Coronation industrials fund class A (CNCG) FUND A
2. Stanlib industrial fund class A (LIIA) FUND B
3. Momentum industrial fund A (RMCF) FUND C
4. Stanlib industrial fund class R (GDKI) FUND D

7.2 Appendix B: ADF and PP/unit root E-views output

Table 40: Large cap level

Null Hypothesis: LARGECAP has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=25)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.779610	0.7145
Test critical values:	1% level	-3.962595	
	5% level	-3.412036	
	10% level	-3.127928	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: LARGECAP has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 12 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-1.535720	0.8172
Test critical values:	1% level	-3.962595	
	5% level	-3.412036	
	10% level	-3.127928	

Table 41: Large cap 1st difference

Null Hypothesis: D(LARGECAP) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=25)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-44.67914	0.0000
Test critical values:	1% level	-3.962598	
	5% level	-3.412037	
	10% level	-3.127929	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(LARGECAP) has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 14 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-45.10064	0.0000
Test critical values:	1% level	-3.962598	
	5% level	-3.412037	
	10% level	-3.127929	

Table 42: Small cap level

Null Hypothesis: SMALLCAP has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 1 (Automatic - based on SIC, maxlag=25)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.167062	0.9937
Test critical values:	1% level	-3.962598	
	5% level	-3.412037	
	10% level	-3.127929	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: SMALLCAP has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 21 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-0.559479	0.9807
Test critical values:	1% level	-3.962595	
	5% level	-3.412036	
	10% level	-3.127928	

Table 43: Small cap 1st difference

Null Hypothesis: D(SMALLCAP) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=25)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-37.79995	0.0000
Test critical values:	1% level	-3.962598	
	5% level	-3.412037	
	10% level	-3.127929	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(SMALLCAP) has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 20 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-40.50853	0.0000
Test critical values:	1% level	-3.962598	
	5% level	-3.412037	
	10% level	-3.127929	

Table 44: Resources level

Null Hypothesis: RESOURCES has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=25)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.921993	0.1556
Test critical values:	1% level	-3.962595	
	5% level	-3.412036	
	10% level	-3.127928	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: RESOURCES has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 4 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-2.910197	0.1593
Test critical values:	1% level	-3.962595	
	5% level	-3.412036	
	10% level	-3.127928	

Table 45: Resources 1st difference

Null Hypothesis: D(RESOURCES) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=25)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-42.70591	0.0000
Test critical values:	1% level	-3.962598	
	5% level	-3.412037	
	10% level	-3.127929	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(RESOURCES) has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 8 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-42.69522	0.0000
Test critical values:	1% level	-3.962598	
	5% level	-3.412037	
	10% level	-3.127929	

Table 46: Value level

Null Hypothesis: VALUE has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=25)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.944985	0.6302
Test critical values:	1% level	-3.962595	
	5% level	-3.412036	
	10% level	-3.127928	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: VALUE has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 14 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-1.730970	0.7373
Test critical values:	1% level	-3.962595	
	5% level	-3.412036	
	10% level	-3.127928	

Table 47: Value 1st difference

Null Hypothesis: D(VALUE) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=25)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-44.39618	0.0000
Test critical values:	1% level	-3.962598	
	5% level	-3.412037	
	10% level	-3.127929	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(VALUE) has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 16 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-44.68407	0.0000
Test critical values:	1% level	-3.962598	
	5% level	-3.412037	
	10% level	-3.127929	

Table 48: Growth level

Null Hypothesis: GROWTH has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=25)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.639408	0.7772
Test critical values:	1% level	-3.962595	
	5% level	-3.412036	
	10% level	-3.127928	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: GROWTH has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 9 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-1.489805	0.8331
Test critical values:	1% level	-3.962595	
	5% level	-3.412036	
	10% level	-3.127928	

Table 49: Growth 1st difference

Null Hypothesis: D(GROWTH) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=25)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-43.91207	0.0000
Test critical values:	1% level	-3.962598	
	5% level	-3.412037	
	10% level	-3.127929	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(GROWTH) has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 11 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-44.08526	0.0000
Test critical values:	1% level	-3.962598	
	5% level	-3.412037	
	10% level	-3.127929	

Table 50: Industrials level

Null Hypothesis: INDUSTRIALS has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=25)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.346759	0.8757
Test critical values:	1% level	-3.962595	
	5% level	-3.412036	
	10% level	-3.127928	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: INDUSTRIALS has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 3 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-1.341000	0.8772
Test critical values:	1% level	-3.962595	
	5% level	-3.412036	
	10% level	-3.127928	

Table 51: Industrials 1st difference

Null Hypothesis: D(INDUSTRIALS) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=2 5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-44.39402	0.0000
Test critical values:	1% level	-3.962598	
	5% level	-3.412037	
	10% level	-3.127929	

Null Hypothesis: D(INDUSTRIALS) has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 1 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-44.39424	0.0000
Test critical values:	1% level	-3.962598	
	5% level	-3.412037	
	10% level	-3.127929	

7.3 Appendix C: Engle-Granger results

7.3.1 Engle-Granger results, Panel A

Table 52: ADF results for Panel A

ADF test on small cap and industrials residuals

Null Hypothesis: USI has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.727964	0.0214
Test critical values:	1% level	-3.976554	
	5% level	-3.418852	
	10% level	-3.131965	

*MacKinnon (1996) one-sided p-values.

ADF test on small cap and resources residuals

Null Hypothesis: USR has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 2 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.621707	0.7833
Test critical values:	1% level	-3.976629	
	5% level	-3.418889	
	10% level	-3.131986	

*MacKinnon (1996) one-sided p-values.

ADF test on small cap and large cap residuals

Null Hypothesis: USL has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.481770	0.8348
Test critical values:	1% level	-3.976554	
	5% level	-3.418852	
	10% level	-3.131965	

*MacKinnon (1996) one-sided p-values.

ADF test on small cap and growth residuals

Null Hypothesis: USG has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.527008	0.8193
Test critical values:	1% level	-3.976554	
	5% level	-3.418852	
	10% level	-3.131965	

*MacKinnon (1996) one-sided p-values.

ADF test on small cap and value residuals

Null Hypothesis: USV has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.058448	0.5672
Test critical values:	1% level	-3.976554	
	5% level	-3.418852	
	10% level	-3.131965	

*MacKinnon (1996) one-sided p-values.

ADF test on industrials and resources residuals

Null Hypothesis: UIR has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.144957	0.5189
Test critical values:	1% level	-3.976554	
	5% level	-3.418852	
	10% level	-3.131965	

*MacKinnon (1996) one-sided p-values.

ADF test on industrials and large cap residuals

Null Hypothesis: UIL has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.952719	0.6250
Test critical values:	1% level	-3.976554	
	5% level	-3.418852	
	10% level	-3.131965	

*MacKinnon (1996) one-sided p-values.

ADF test on industrials and growth

Null Hypothesis: UIG has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.100575	0.5437
Test critical values:	1% level	-3.976554	
	5% level	-3.418852	
	10% level	-3.131965	

*MacKinnon (1996) one-sided p-values.

ADF test on industrials and value residuals

Null Hypothesis: UIV has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.735128	0.7343
Test critical values:	1% level	-3.976554	
	5% level	-3.418852	
	10% level	-3.131965	

*MacKinnon (1996) one-sided p-values.

ADF test on resources and large cap residuals

Null Hypothesis: URL has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.715092	0.2309
Test critical values:	1% level	-3.976554	
	5% level	-3.418852	
	10% level	-3.131965	

*MacKinnon (1996) one-sided p-values.

ADF test on resources and growth residuals

Null Hypothesis: URG has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.545919	0.3058
Test critical values:	1% level	-3.976554	
	5% level	-3.418852	
	10% level	-3.131965	

*MacKinnon (1996) one-sided p-values.

ADF test on resources and value residuals

Null Hypothesis: URV has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 1 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.322190	0.4206
Test critical values:	1% level	-3.976591	
	5% level	-3.418870	
	10% level	-3.131976	

*MacKinnon (1996) one-sided p-values.

ADF test on large cap and growth residuals

Null Hypothesis: ULG has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.142956	0.0976
Test critical values:	1% level	-3.976554	
	5% level	-3.418852	
	10% level	-3.131965	

*MacKinnon (1996) one-sided p-values.

ADF test on large cap and value residuals

Null Hypothesis: ULV has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.003637	0.5974
Test critical values:	1% level	-3.976554	
	5% level	-3.418852	
	10% level	-3.131965	

*MacKinnon (1996) one-sided p-values.

ADF test on growth and value residuals

Null Hypothesis: UGV has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 1 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.732688	0.2238
Test critical values:	1% level	-3.976591	
	5% level	-3.418870	
	10% level	-3.131976	

*MacKinnon (1996) one-sided p-values.

7.3.2 Engle-Granger results, Panel B

Table 53: ADF results for Panel B

ADF test on small cap and industrials residuals

Null Hypothesis: USI has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.697238	0.0008
Test critical values:	1% level	-3.976554	
	5% level	-3.418852	
	10% level	-3.131965	

*MacKinnon (1996) one-sided p-values.

ADF test on small cap and resources residuals

Null Hypothesis: USR has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.861058	0.0143
Test critical values:	1% level	-3.976554	
	5% level	-3.418852	
	10% level	-3.131965	

*MacKinnon (1996) one-sided p-values.

ADF test on small cap and large cap residuals

Null Hypothesis: USL has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.543084	0.0014
Test critical values:	1% level	-3.976554	
	5% level	-3.418852	
	10% level	-3.131965	

*MacKinnon (1996) one-sided p-values.

ADF test on small cap and growth residuals

Null Hypothesis: USG has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.135615	0.0001
Test critical values:	1% level	-3.976554	
	5% level	-3.418852	
	10% level	-3.131965	

*MacKinnon (1996) one-sided p-values.

ADF test on small cap and value residuals

Null Hypothesis: USV has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.164338	0.0929
Test critical values:	1% level	-3.976554	
	5% level	-3.418852	
	10% level	-3.131965	

*MacKinnon (1996) one-sided p-values.

ADF test on industrials and resources residuals

Null Hypothesis: UIR has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.835891	0.1850
Test critical values:	1% level	-3.976554	
	5% level	-3.418852	
	10% level	-3.131965	

*MacKinnon (1996) one-sided p-values.

ADF test on industrials and large cap residuals

Null Hypothesis: UIL has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.927608	0.1546
Test critical values:	1% level	-3.976554	
	5% level	-3.418852	
	10% level	-3.131965	

*MacKinnon (1996) one-sided p-values.

ADF test on industrials and growth

Null Hypothesis: UIG has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.451743	0.0459
Test critical values:	1% level	-3.976554	
	5% level	-3.418852	
	10% level	-3.131965	

*MacKinnon (1996) one-sided p-values.

ADF test on industrials and value residuals

Null Hypothesis: UIV has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.780472	0.2052
Test critical values:	1% level	-3.976554	
	5% level	-3.418852	
	10% level	-3.131965	

*MacKinnon (1996) one-sided p-values.

ADF test on resources and large cap residuals

Null Hypothesis: URL has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.492455	0.0412
Test critical values:	1% level	-3.976554	
	5% level	-3.418852	
	10% level	-3.131965	

*MacKinnon (1996) one-sided p-values.

ADF test on resources and growth residuals

Null Hypothesis: URG has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.456172	0.3500
Test critical values:	1% level	-3.976554	
	5% level	-3.418852	
	10% level	-3.131965	

*MacKinnon (1996) one-sided p-values.

ADF test on resources and value residuals

Null Hypothesis: URV has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.050183	0.0079
Test critical values:	1% level	-3.976554	
	5% level	-3.418852	
	10% level	-3.131965	

*MacKinnon (1996) one-sided p-values.

ADF test on large cap and growth residuals

Null Hypothesis: ULG has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.325811	0.0633
Test critical values:	1% level	-3.976554	
	5% level	-3.418852	
	10% level	-3.131965	

*MacKinnon (1996) one-sided p-values.

ADF test on large cap and value residuals

Null Hypothesis: ULV has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.278468	0.0036
Test critical values:	1% level	-3.976554	
	5% level	-3.418852	
	10% level	-3.131965	

*MacKinnon (1996) one-sided p-values.

ADF test on growth and value residuals

Null Hypothesis: UGV has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.021154	0.0087
Test critical values:	1% level	-3.976554	
	5% level	-3.418852	
	10% level	-3.131965	

*MacKinnon (1996) one-sided p-values.

7.3.3 Engle Granger results, Panel C

Table 54: ADF results for Panel C

ADF test on small cap and industrials residuals

Null Hypothesis: USI has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.772793	0.0006
Test critical values:	1% level	-3.976480	
	5% level	-3.418816	
	10% level	-3.131943	

*MacKinnon (1996) one-sided p-values.

ADF test on small cap and resources residuals

Null Hypothesis: USR has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.227479	0.4727
Test critical values:	1% level	-3.976480	
	5% level	-3.418816	
	10% level	-3.131943	

*MacKinnon (1996) one-sided p-values.

ADF test on small cap and large cap residuals

Null Hypothesis: USL has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.887617	0.0132
Test critical values:	1% level	-3.976480	
	5% level	-3.418816	
	10% level	-3.131943	

*MacKinnon (1996) one-sided p-values.

ADF test on small cap and growth residuals

Null Hypothesis: USG has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.200197	0.0048
Test critical values:	1% level	-3.976480	
	5% level	-3.418816	
	10% level	-3.131943	

*MacKinnon (1996) one-sided p-values.

ADF test on small cap and value residuals

Null Hypothesis: USV has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.476979	0.0430
Test critical values:	1% level	-3.976480	
	5% level	-3.418816	
	10% level	-3.131943	

*MacKinnon (1996) one-sided p-values.

ADF test on industrials and resources residuals

Null Hypothesis: UIR has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.332461	0.4150
Test critical values:	1% level	-3.976480	
	5% level	-3.418816	
	10% level	-3.131943	

*MacKinnon (1996) one-sided p-values.

ADF test on industrials and large cap residuals

Null Hypothesis: UIL has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.505020	0.3256
Test critical values:	1% level	-3.976480	
	5% level	-3.418816	
	10% level	-3.131943	

*MacKinnon (1996) one-sided p-values.

ADF test on industrials and growth

Null Hypothesis: UIG has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.839028	0.1839
Test critical values:	1% level	-3.976480	
	5% level	-3.418816	
	10% level	-3.131943	

*MacKinnon (1996) one-sided p-values.

ADF test on industrials and value residuals

Null Hypothesis: UIV has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.017205	0.5900
Test critical values:	1% level	-3.976480	
	5% level	-3.418816	
	10% level	-3.131943	

*MacKinnon (1996) one-sided p-values.

ADF test on resources and large cap residuals

Null Hypothesis: URL has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.334091	0.0620
Test critical values:	1% level	-3.976480	
	5% level	-3.418816	
	10% level	-3.131943	

*MacKinnon (1996) one-sided p-values.

ADF test on resources and growth residuals

Null Hypothesis: URG has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.402582	0.0521
Test critical values:	1% level	-3.976480	
	5% level	-3.418816	
	10% level	-3.131943	

*MacKinnon (1996) one-sided p-values.

ADF test on resources and value residuals

Null Hypothesis: URV has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.450951	0.0460
Test critical values:	1% level	-3.976480	
	5% level	-3.418816	
	10% level	-3.131943	

*MacKinnon (1996) one-sided p-values.

ADF test on large cap and growth residuals

Null Hypothesis: ULG has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 1 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.396287	0.3810
Test critical values:	1% level	-3.976517	
	5% level	-3.418834	
	10% level	-3.131954	

*MacKinnon (1996) one-sided p-values.

ADF test on large cap and value residuals

Null Hypothesis: ULV has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.728745	0.2254
Test critical values:	1% level	-3.976480	
	5% level	-3.418816	
	10% level	-3.131943	

*MacKinnon (1996) one-sided p-values.

ADF test on growth and value residuals

Null Hypothesis: UGV has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.746918	0.7288
Test critical values:	1% level	-3.976480	
	5% level	-3.418816	
	10% level	-3.131943	

*MacKinnon (1996) one-sided p-values.

7.3.4 Engle Granger results, Panel D

Table 55: ADF results for Panel D

ADF test on small cap and industrials residuals

Null Hypothesis: USI has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 1 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.894799	0.1650
Test critical values:	1% level	-3.975976	
	5% level	-3.418570	
	10% level	-3.131798	

*MacKinnon (1996) one-sided p-values.

ADF test on small cap and resources residuals

Null Hypothesis: USR has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.859329	0.6740
Test critical values:	1% level	-3.975941	
	5% level	-3.418553	
	10% level	-3.131788	

*MacKinnon (1996) one-sided p-values.

ADF test on small cap and large cap residuals

Null Hypothesis: USL has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.020203	0.1276
Test critical values:	1% level	-3.975941	
	5% level	-3.418553	
	10% level	-3.131788	

*MacKinnon (1996) one-sided p-values.

ADF test on small cap and growth residuals

Null Hypothesis: USG has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.135948	0.0991
Test critical values:	1% level	-3.975941	
	5% level	-3.418553	
	10% level	-3.131788	

*MacKinnon (1996) one-sided p-values.

ADF test on small cap and value residuals

Null Hypothesis: USV has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.107881	0.1055
Test critical values:	1% level	-3.975941	
	5% level	-3.418553	
	10% level	-3.131788	

*MacKinnon (1996) one-sided p-values.

ADF test on industrials and resources residuals

Null Hypothesis: UIR has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.846307	0.6807
Test critical values:	1% level	-3.975941	
	5% level	-3.418553	
	10% level	-3.131788	

*MacKinnon (1996) one-sided p-values.

ADF test on industrials and large cap residuals

Null Hypothesis: UIL has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.004244	0.5971
Test critical values:	1% level	-3.975941	
	5% level	-3.418553	
	10% level	-3.131788	

*MacKinnon (1996) one-sided p-values.

ADF test on industrials and growth

Null Hypothesis: UIG has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.138263	0.5227
Test critical values:	1% level	-3.975941	
	5% level	-3.418553	
	10% level	-3.131788	

*MacKinnon (1996) one-sided p-values.

ADF test on industrials and value residuals

Null Hypothesis: UIV has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.861994	0.6727
Test critical values:	1% level	-3.975941	
	5% level	-3.418553	
	10% level	-3.131788	

*MacKinnon (1996) one-sided p-values.

ADF test on resources and large cap residuals

Null Hypothesis: URL has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.731836	0.7358
Test critical values:	1% level	-3.975941	
	5% level	-3.418553	
	10% level	-3.131788	

*MacKinnon (1996) one-sided p-values.

ADF test on resources and growth residuals

Null Hypothesis: URG has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.709079	0.7461
Test critical values:	1% level	-3.975941	
	5% level	-3.418553	
	10% level	-3.131788	

*MacKinnon (1996) one-sided p-values.

ADF test on resources and value residuals

Null Hypothesis: URV has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.858590	0.6744
Test critical values:	1% level	-3.975941	
	5% level	-3.418553	
	10% level	-3.131788	

*MacKinnon (1996) one-sided p-values.

ADF test on large cap and growth residuals

Null Hypothesis: ULG has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.359365	0.0027
Test critical values:	1% level	-3.975941	
	5% level	-3.418553	
	10% level	-3.131788	

*MacKinnon (1996) one-sided p-values.

ADF test on large cap and value residuals

Null Hypothesis: ULV has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.179201	0.0898
Test critical values:	1% level	-3.975941	
	5% level	-3.418553	
	10% level	-3.131788	

*MacKinnon (1996) one-sided p-values.

ADF test on growth and value residuals

Null Hypothesis: UGV has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.536264	0.0366
Test critical values:	1% level	-3.975941	
	5% level	-3.418553	
	10% level	-3.131788	

*MacKinnon (1996) one-sided p-values.

7.3.5 Engle-Granger results, Panel E

Table 56: ADF results for Panel E

ADF test on small cap and industrials residuals

Null Hypothesis: USI has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 1 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.433398	0.0019
Test critical values:	1% level	-3.962598	
	5% level	-3.412037	
	10% level	-3.127929	

*MacKinnon (1996) one-sided p-values.

ADF test on small cap and resources residuals

Null Hypothesis: USR has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.118996	0.9243
Test critical values:	1% level	-3.962595	
	5% level	-3.412036	
	10% level	-3.127928	

*MacKinnon (1996) one-sided p-values.

ADF test on small cap and large cap residuals

Null Hypothesis: USL has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.008869	0.0086
Test critical values:	1% level	-3.962595	
	5% level	-3.412036	
	10% level	-3.127928	

*MacKinnon (1996) one-sided p-values.

ADF test on small cap and growth residuals

Null Hypothesis: USG has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.021329	0.0083
Test critical values:	1% level	-3.962595	
	5% level	-3.412036	
	10% level	-3.127928	

*MacKinnon (1996) one-sided p-values.

ADF test on small cap and value residuals

Null Hypothesis: USV has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 4 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.966263	0.6188
Test critical values:	1% level	-3.962605	
	5% level	-3.412041	
	10% level	-3.127931	

*MacKinnon (1996) one-sided p-values.

ADF test on industrials and resources residuals

Null Hypothesis: UIR has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 1 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.562889	0.8073
Test critical values:	1% level	-3.962598	
	5% level	-3.412037	
	10% level	-3.127929	

*MacKinnon (1996) one-sided p-values.

ADF test on industrials and large cap residuals

Null Hypothesis: UIL has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.011138	0.1293
Test critical values:	1% level	-3.962595	
	5% level	-3.412036	
	10% level	-3.127928	

*MacKinnon (1996) one-sided p-values.

ADF test on industrials and growth

Null Hypothesis: UIG has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.287405	0.0686
Test critical values:	1% level	-3.962595	
	5% level	-3.412036	
	10% level	-3.127928	

*MacKinnon (1996) one-sided p-values.

ADF test on industrials and value residuals

Null Hypothesis: UIV has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.182147	0.4988
Test critical values:	1% level	-3.962595	
	5% level	-3.412036	
	10% level	-3.127928	

*MacKinnon (1996) one-sided p-values.

ADF test on resources and large cap residuals

Null Hypothesis: URL has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 1 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.196424	0.0854
Test critical values:	1% level	-3.962598	
	5% level	-3.412037	
	10% level	-3.127929	

*MacKinnon (1996) one-sided p-values.

ADF test on resources and growth residuals

Null Hypothesis: URG has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.918442	0.1567
Test critical values:	1% level	-3.962595	
	5% level	-3.412036	
	10% level	-3.127928	

*MacKinnon (1996) one-sided p-values.

ADF test on resources and value residuals

Null Hypothesis: URV has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 1 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.219075	0.0809
Test critical values:	1% level	-3.962598	
	5% level	-3.412037	
	10% level	-3.127929	

*MacKinnon (1996) one-sided p-values.

ADF test on large cap and growth residuals

Null Hypothesis: ULG has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.115619	0.1028
Test critical values:	1% level	-3.962595	
	5% level	-3.412036	
	10% level	-3.127928	

*MacKinnon (1996) one-sided p-values.

ADF test on large cap and value residuals

Null Hypothesis: ULV has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.875956	0.6666
Test critical values:	1% level	-3.962595	
	5% level	-3.412036	
	10% level	-3.127928	

*MacKinnon (1996) one-sided p-values.

ADF test on growth and value residuals

Null Hypothesis: UGV has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.054077	0.5706
Test critical values:	1% level	-3.962595	
	5% level	-3.412036	
	10% level	-3.127928	

*MacKinnon (1996) one-sided p-values.

7.4 Appendix D: Correlation matrix results

7.4.1 Segregated periods method results

FIRST 2 YEARS

Covariance Analysis: Ordinary
Sample: 9/08/2006 9/05/2008
Included observations: 499

Correlation Probability	GROWTHr	INDUSTRIALSr	LARGECAPr	RESOURCEr	SMALLCAPr	VALUEr
GROWTHr	1.000000 -----					
INDUSTRIALSr	0.605300 0.0000	1.000000 -----				
LARGECAPr	0.957818 0.0000	0.699495 0.0000	1.000000 -----			
RESOURCESr	0.929903 0.0000	0.478557 0.0000	0.924536 0.0000	1.000000 -----		
SMALLCAPr	0.539272 0.0000	0.594639 0.0000	0.568271 0.0000	0.469743 0.0000	1.000000 -----	
VALUEr	0.839135 0.0000	0.770652 0.0000	0.954626 0.0000	0.830308 0.0000	0.619440 0.0000	1.000000 -----

SECOND 2 YEARS

Covariance Analysis: Ordinary
Sample: 9/08/2008 9/07/2010
Included observations: 499

Correlation Probability	GROWTHr	INDUSTRIALSr	LARGECAPr	RESOURCEr	SMALLCAPr	VALUEr
GROWTHr	1.000000 -----					
INDUSTRIALSr	0.758215 0.0000	1.000000 -----				
LARGECAPr	0.982552 0.0000	0.793599 0.0000	1.000000 -----			
RESOURCESr	0.957678 0.0000	0.687261 0.0000	0.955291 0.0000	1.000000 -----		
SMALLCAPr	0.586736 0.0000	0.588254 0.0000	0.601360 0.0000	0.561315 0.0000	1.000000 -----	
VALUEr	0.903288 0.0000	0.9832818 0.0000	0.964763 0.0000	0.888286 0.0000	0.634828 0.0000	1.000000 -----

THIRD 2 YEARS

Covariance Analysis: Ordinary
Sample: 9/08/2010 9/07/2012
Included observations: 501

Correlation Probability	GROWTHr	INDUSTRIALSr	LARGECAPr	RESOURCEr	SMALLCAPr	VALUEr
GROWTHr	1.000000 -----					
INDUSTRIALSr	0.742303 0.0000	1.000000 -----				
LARGECAPr	0.980566 0.0000	0.771095 0.0000	1.000000 -----			
RESOURCESr	0.920049 0.0000	0.629944 0.0000	0.932149 0.0858	1.000000 -----		
SMALLCAPr	0.489969 0.0000	0.518589 0.0000	0.486889 0.0000	0.472932 0.0000	1.000000 -----	
VALUEr	0.917268 0.0000	0.811207 0.0000	0.970764 0.0000	0.889796 0.0473	0.519475 0.0000	1.000000 -----

FOURTH 2 YEARS

Covariance Analysis: Ordinary
Sample: 9/10/2012 10/06/2014
Included observations: 516

Correlation Probability	GROWTHr	INDUSTRIALSr	LARGECAPr	RESOURCEr	SMALLCAPr	VALUEr
GROWTHr	1.000000 -----					
INDUSTRIALSr	0.633170 0.0000	1.000000 -----				
LARGECAPr	0.985294 0.0000	0.685949 0.0000	1.000000 -----			
RESOURCESr	0.814212 0.0000	0.401200 0.0000	0.818651 0.0000	1.000000 -----		
SMALLCAPr	0.542397 0.0000	0.535218 0.0000	0.537093 0.0000	0.375211 0.0000	1.000000 -----	
VALUEr	0.792125 0.0000	0.820393 0.0000	0.872458 0.0000	0.642137 0.0000	0.556536 0.0000	1.000000 -----

8 YEAR PERIOD (Overall period)

Covariance Analysis: Ordinary
Sample: 9/08/2006 10/06/2014
Included observations: 2018

Correlation Probability	GROWTHr	INDUSTRIALSr	LARGECAPr	RESOURCEr	SMALLCAPr	VALUEr
GROWTHr	1.000000 -----					
INDUSTRIALSr	0.693328 0.0000	1.000000 -----				
LARGECAPr	0.975410 0.0000	0.747139 0.0000	1.000000 -----			
RESOURCESr	0.930138 0.0000	0.582425 0.0000	0.929647 0.0000	1.000000 -----		
SMALLCAPr	0.550452 0.0000	0.571620 0.0000	0.563562 0.0000	0.496803 0.0000	1.000000 -----	
VALUEr	0.877001 0.0000	0.807095 0.0000	0.953911 0.0000	0.847562 0.0000	0.600647 0.0000	1.000000 -----

7.4.2 Roll-over method results

FIRST CYCLE

Covariance Analysis: Ordinary
Sample: 9/08/2006 9/05/2008
Included observations: 500

Correlation Probability	GROWTHr	INDUSTRIALSr	LARGECAPr	RESOURCEr	SMALLCAPr	VALUEr
GROWTHr	1.000000 -----					
INDUSTRIALSr	0.605300 0.0000	1.000000 -----				
LARGECAPr	0.957818 0.0000	0.699495 0.0000	1.000000 -----			
RESOURCESr	0.929903 0.0000	0.478557 0.0000	0.924536 0.0000	1.000000 -----		
SMALLCAPr	0.539272 0.0000	0.594639 0.0000	0.568271 0.0000	0.469743 0.0000	1.000000 -----	
VALUEr	0.839135 0.0000	0.770652 0.0000	0.954626 0.0000	0.830308 0.0000	0.619440 0.0000	1.000000 -----

SECOND CYCLE

Covariance Analysis: Ordinary
Sample: 9/08/2006 9/07/2010
Included observations: 1000

Correlation Probability	GROWTHr	INDUSTRIALSr	LARGECAPr	RESOURCEr	SMALLCAPr	VALUEr
GROWTHr	1.000000 -----					
INDUSTRIALSr	0.699346 0.0000	1.000000 -----				
LARGECAPr	0.973831 0.0000	0.756855 0.0000	1.000000 -----			
RESOURCESr	0.947388 0.0000	0.608498 0.0000	0.944796 0.0000	1.000000 -----		
SMALLCAPr	0.565146 0.0000	0.590114 0.0000	0.584553 0.0000	0.523167 0.0000	1.000000 -----	
VALUEr	0.880893 0.0000	0.807878 0.0000	0.961253 0.0000	0.774793 0.0000	0.625503 0.0000	1.000000 -----

THIRD CYCLE

Covariance Analysis: Ordinary
Sample: 9/08/2006 9/07/2012
Included observations: 1502

Correlation Probability	GROWTHr	INDUSTRIALSr	LARGECAPr	RESOURCEr	SMALLCAPr	VALUEr
GROWTHr	1.000000 -----					
INDUSTRIALSr	0.704898 0.0000	1.000000 -----				
LARGECAPr	0.974531 0.0000	0.758567 0.0000	1.000000 -----			
RESOURCESr	0.943397 0.0000	0.610416 0.0000	0.942400 0.0000	1.000000 -----		
SMALLCAPr	0.553551 0.0000	0.577881 0.0000	0.568652 0.0000	0.515134 0.0000	1.000000 -----	
VALUEr	0.886124 0.0000	0.807973 0.0000	0.962788 0.0000	0.871228 0.0000	0.608202 0.0000	1.000000 -----

OVERALL PERIOD

Covariance Analysis: Ordinary
Sample: 9/08/2006 10/06/2014
Included observations: 2019

Correlation Probability	GROWTHr	INDUSTRIALSr	LARGECAPr	RESOURCEr	SMALLCAPr	VALUEr
GROWTHr	1.000000 -----					
INDUSTRIALSr	0.693328 0.0000	1.000000 -----				
LARGECAPr	0.975410 0.0000	0.747139 0.0000	1.000000 -----			
RESOURCESr	0.930138 0.0000	0.582425 0.0000	0.929647 0.0000	1.000000 -----		
SMALLCAPr	0.550452 0.0000	0.571620 0.0000	0.563562 0.0000	0.496803 0.0000	1.000000 -----	
VALUEr	0.877001 0.0000	0.807095 0.0000	0.953911 0.0000	0.847562 0.0000	0.600647 0.0000	1.000000 -----