THE PORTFOLIO CONSTRUCTION IMPLICATIONS OF USING VARIOUS SMART BETA FUNDAMENTALS AND THE FUNDAMENTAL-CLASSIFICATION PERSISTENCE OF STOCKS

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Abstract

South African investors have been slow to adopt the smart beta investment style as a new investment vehicle compared to their counterparts in the rest of the world. This predisposition towards smart beta is probably because of its lack of a successful track record and transparency (Cox, 2014). This study attempted to provide insight into both the portfolio construction characteristics of local smart beta funds and the classification persistence of stocks using various fundamental factors.

Six established fundamental factors, namely value, profitability, momentum, investment, liquidity and high yield, were selected to simulate six single- and two multifactor smart beta portfolios. The 'winner' and 'loser' portfolios of each factor were analysed both separately and in combination with each other. One multifactor portfolio applied an equal-weighting to factors by using the equally weighted multifactor fund (EWMF), while the other portfolio was constructed to assign a bigger weighting to factors that recently performed well, using the fundamental factor performance history weighted (FFPHW). A ten-year history was used and the 100 largest stocks listed on the Johannesburg Stock Exchange (JSE) on a monthly basis were eligible to be included in the selection of 30 winner and loser stock portfolios.

The FFPHW contributes to the existing body of knowledge on constructing smart beta portfolios. The FFPHW methodology was implemented to test the potential of adding value when assigning weights to fundamental factors based on their individual prior performance. The FFPHW strategy was tested against the SWIX and managed to produce an annualised 2.9 per cent market-adjusted abnormal after-cost return over a ten-year period. Against expectation, the equal-weighted strategy significantly outperformed the FFPHW portfolio by achieving an annualised 6.2 per cent market-adjusted abnormal after-cost return. Assigning equal weights to individual fundamental factors in a multifactor portfolio is therefore preferred.

The individual fundamental factors that drive returns in the two multifactor portfolios were also tested. Similar to Hou, Xue and Zhang (2016), the profitability factor proved to be a dominating driving force of returns in the multifactor portfolios. The momentum fundamental factor also proved to be a significant driver of returns, which is in contrast with what Van Heerden (2014) reported. The investment and liquidity fundamental factors proved to have limited investment value as they failed to consistently identify the potential outperforming stocks.

An analysis of the relationships that may hold between i) net returns, ii) portfolio churn and iii) classification persistence under various portfolio rebalancing strategies was conducted to provide insights into the practical implications of constructing smart beta fund portfolios. A decreasing marginal benefit of return was found for extending the periods between portfolio rebalancing activities. Quarterly rebalancing proved to be the optimal rebalancing strategy as it captures short-lived profits before the stock prices mean-revert.

The classification persistence of stocks was also analysed. Classification persistence is defined as the probability of a stock persisting under its existing winner (buy), neutral or loser (sell) classification for the following period given that it already persisted for four, five or six months. The classification persistence of stocks proved to be extremely high once the stock has already persisted for at least four months. No significant difference in the classification persistence of stocks across various sectors could be noted. The winner portfolios, however, proved to display lower classification persistence than the loser portfolios. So-called ‘bad’ stocks are therefore more likely to remain ‘bad’ than ‘good’ stocks are to remain ‘good’.

Even though the study found that smart beta offered investors a profitable long-term strategy over a ten year period of 2007 - 2016, smart beta strategies struggled to outperform the SWIX from 2012 onwards. Overall, the study concluded that the costs involved in executing portfolio decisions did not outweigh the benefits, that winner and loser portfolios did not change very often, and that the fundamental factor interaction provided additional investment value.

Key words:

Smart beta

Fundamental indexing

Factor investing

Classification persistence

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List of acronyms and abbreviations

ALSI	JSE FTSE All Share Index
ANOVA	analysis of variance
APT	arbitrage pricing theory
AUM	assets under management
BPS	basis points
CAPM	capital asset pricing model
EMH	efficient market hypothesis
ETF	exchange trading fund
EWMF	equally weighted multifactor
FDI	foreign direct investment
FFPHW	fundamental factor performance history weighted
GDP	gross domestic product
HML	high-minus-low
HY	high yield fundamental factor
IML	illiquid minus liquid
INV	investment fundamental factor
LASSO	least absolute shrinkage and selection operator
LIQ	liquidity fundamental factor
MOM	momentum fundamental factor
MSCI	Morgan Stanley Capital International
PE	price-to-earnings
PROF	profitability fundamental factor
RMW	robust minus weak
ROE	return on equity
STT	securities transaction costs
SWIX	Shareholder Weighted All Share Index
US	United States (of America)
VAL	value fundamental factor
VAT	value-added tax

CHAPTER 1

INTRODUCTION TO SMART BETA AS AN INVESTMENT PHILOSOPHY

1.1 INTRODUCTION

Smart beta funds have experienced a considerable growth of 73 per cent in global assets under management (AUM) from 2009 (BlackRock, 2017). Leading firms in the investment industry, such as BlackRock, predict an annual organic growth of around 19 per cent to reach $1 trillion worth in exchange trading funds (ETF) smart beta assets globally by 2020 (BlackRock, 2017). This growth is expected to be driven largely by the advances in data analytics and technology which allow investors to access a market that was previously only accessible to large asset houses. The exceptional growth of smart beta funds has attracted global attention that is directed towards smart beta and specifically its advantages and disadvantages. The question therefore arises: how does one obtain the maximum benefit from a smart beta strategy?

The success of smart beta, or so-called ‘factor investing’, is primarily attributed to its ability to disregard the market capitalisation weighted strategy in favour of an equal- or fundamentally weighted strategy (Arnott, 2016). The smart beta fund is therefore unburdened by the inherent flaw of a market capitalisation weighted strategy to overweight the over-priced stocks and underweight the under-priced stocks. In contrast to this strategy, smart beta seeks to outperform traditional passive indices by following a fundamental factor-led investment philosophy. In other words, proven fundamental factors are applied to identify stocks which are believed to have the inherent requirements that should lead to outperformance. A portfolio algorithm is therefore constructed to periodically rebalance the smart beta portfolio to the desired weights in each fundamental factor identified stock.

Rob Arnott, who is known as the ‘godfather of smart beta investing’, has recently warned against what is perceived by the market as smart beta and how it can go terribly awry for investors (Arnott, 2016). The primary reason for this warning is the lack of a proven track record and transparency of these funds. Due to a lack of transparency, the interrelationships in a smart beta strategy are mostly unknown (Cox, 2014). Smart beta fund managers may therefore find it difficult to construct optimal funds, which in turn may lead to smart beta fund managers failing to unlock the potential benefits of smart beta as an investment philosophy. This study therefore attempted to provide additional transparency of the fund management process and the implications of decisions pertaining to different smart beta portfolio constructions.

1.2 BACKGROUND TO THE STUDY

Smart beta has become an umbrella term to many different investment strategies. Arnott (2016) argues that a fund cannot claim to be a true smart beta strategy if it is still tied to any market capitalisation weighted strategy. The disconnection with stock price weighting schemes, which leads to oversensitivity to larger stocks, is therefore the deciding factor whether or not a fund may be classified as smart beta. Smart beta fund characteristics will subsequently be discussed to provide a sufficient background to why this study was conducted.

1.2.1 Fundamental factors

Fundamental factors are nowadays common observed as many researchers and industry professionals have attempted to uncover previously unnoticed anomalies in equity returns and/or methods of quantifying these anomalies. Beck, Hsu, Kalesnik and Kostka (2016) estimate that around 300 quantitative fundamental factors have already been published, with around 40 new factors being published each year. These anomalies are then implemented within a factor investment strategy in the hope of offering outperformance. Some smart beta professionals instead prefer to trade based on established fundamental factors such as those described by Fama and French (1998, 2006) in their three-factor model, and later their five-factor model. The use of these asset pricing models was an extension of the initial capital asset pricing model (CAPM) to also include value, size, profitability and investment. Other well-known fundamental factors include momentum (Jegadeesh & Titman, 1993), liquidity (Pástor & Stambaugh, 2003), investment (Fama & French, 2006), high yield (Graham & Dodd, 1951) and low volatility (Clarke, de Silva & Thorley, 2006).

In order to construct a smart beta portfolio, a fundamental factor selection must first take place as well as certain portfolio construction decisions. The funds are considered to be indexed, passive funds overall. As soon as the algorithm for investing is decided upon, the fund will function as a passive fund. These initial fund management decisions are of interest in this study as such decisions aim to determine how to optimise smart beta portfolio management when constructing a smart beta portfolio. However, a fundamental factor selection is not the focus of this study as extensive research has already been conducted on the topic (for example Zhang 2005; Van Heerden, 2014; Amenc, Lodh, Le Sourd & Goltz 2015 and Hou, Xue & Zhang, 2016). Instead, the current study questions the fund management process once the fundamental factors have been selected.

Once the fundamental factors have been selected, the fund manager can trade based on the information derived from the fundamental factor signals. These so-called 'signals' refer to winner (buy), or neutral or loser (sell) classifications awarded to each stock, based on the fundamental factor requirements. For instance, the profitability factor as measured by the return on equity (ROE) ratio suggests that stocks with a higher ROE will outperform those with a lower ROE (Fama & French, 2006). The stocks within the portfolio investment horizon with the highest ROE's will therefore be classified as winners or buy signals. Stocks with the lowest ROEs will be classified as losers or sell signals. The smart beta portfolio then periodically trades on these signals in the hope to profit from the inherent value of the information derived from the profitability factor. The investment value is indicated by the ability of these signals to accurately and consistently identify outperforming stocks. In order to unlock these returns, which are made possible by the investment value derived from the selected fundamental factors, the portfolio must trade on these signals. As a result, trading costs are incurred.

1.2.2 Trade-off between unlocking returns through exposure to fundamental factor signals and trading costs

Globally, smart beta outperformance has been partly ascribed to the lower fees when compared to the fees of actively managed funds. The low fees are, however, largely possible due to the depth, or liquidity, of developed financial markets. Emerging markets, such as the South African market, find it difficult to offer competitive fees as the cost of trading is more expensive due to less liquid markets. It is yet to be seen whether the cost benefit inherent to smart beta funds in developed markets materialise in the South African market. This study therefore assessed the marginal benefit of return that transpires due to increased trading costs incurred in an attempt to benefit from the fundamental factor signals.

1.3 METHODOLOGY

Given that a smart beta fund functions passively with the help of an algorithm, the initial decisions that are made are crucial to the fund's success. The decisions driving the algorithm broadly fall into two categories, namely fundamental factor selection and portfolio implementation decisions. Although the selected fundamental factors were evaluated, the focus of this study remains on the latter decision-making category. More specifically, the study investigated the simulated smart beta portfolios to assess the interrelationships that arise from the different single- and multifactor strategies.

Firstly, six single-factor portfolios were constructed using the following fundamental factors: i) value, ii) profitability, iii) momentum, iv) liquidity, v) investment and vi) high yield. Secondly, two multifactor strategies were constructed, both incorporating all six fundamental factors, but with two very different portfolio construction methodologies: an equally weighted multifactor (EWMF) fund and a fundamental factor performance history weighted (FFPHW) fund. The difference between the two portfolios is how each portfolio consolidates the fundamental factor signals to determine which stocks to include or exclude from the portfolio. The EWMF portfolio assigns equal weights to all fundamental factor signals, whereas the FFPHW portfolio weights the signals relative to their recent performance. This weighting strategy was followed to test if 'listening' to the best signals as they change over time would yield superior results. This strategy is a new contribution to the existing body of knowledge on smart beta.

1.3.1 Research objectives

Once the simulated portfolios were constructed, it was possible to give effect to the research objectives. Primarily, this study attempted to provide further insight into smart beta funds and thereby address the lack of transparency concern raised by Cox (2014). Research objectives were established to systematically and effectively give effect to the relevant research questions raised.

The primary research objectives were to investigate smart beta stock-classification patterns and to investigate the practical portfolio rebalancing implications of having to buy or sell certain stocks periodically. The classification persistence of stocks therefore provided increased transparency into the smart beta portfolios.

The research objectives were developed to systematically address the primary research problem. The primary research objective is two-fold: firstly, to investigate the practical portfolio rebalancing implications of having to buy or sell certain stocks periodically and secondly, to investigate smart beta stock-classification patterns. The effects of implementing various rebalancing frequencies on the portfolio include the resultant portfolio churn and secondly, the after-cost performance over the 2007 to 2016 period.

The goal of the secondary objectives is to guide the primary objective. The secondary objectives are:

I. to measure the effect of rebalancing according to various calendar intervals on the net returns of simulated portfolios;
II. to compare each simulated smart beta portfolio's after-cost performance to relevant benchmarks;
III. to identify the main fundamental factor(s) driving returns across the two multifactor portfolio strategies;
IV. to analyse the relationship of portfolio turnover (called churn) with portfolio return and stock classification persistence;
V. to measure the probability that a stock that was included in a winner (loser) portfolio for N consecutive months, will remain in the winner (loser) portfolio for N+1 months (N= four-, five-, and six months);
VI. to compare the classification persistence stability of the best-rated stocks to that of the worst-rated stocks; and
VII. to determine the probability of classification persistence within specific market sectors.

1.4 CONTRIBUTIONS

By addressing the proposed research objectives, this study contributes to the existing body of knowledge on smart beta. However, the focus is on the South African context as smart beta research has previously focused primarily on developed markets. By providing insight into smart beta funds in the South African context, this study will assist investment professionals in their attempts to offer outperformance by means of smart beta investment strategies.

As far as the researcher could ascertain, no previous research has been conducted on the classification persistence of stocks in the South African environment. This study thus addresses the transparency issue and may assist smart beta professionals to optimise their smart beta portfolio construction process.

1.5 CONCLUSION

The existing body of knowledge on smart beta investing fails to provide sufficient insight into the relationships that are present within these strategies. Cox (2014) suggests that the lack of transparency of these strategies is a major stumbling block for smart beta. In an attempt to provide insight into smart beta portfolios, this study examined the classification persistence of stocks and the resultant relationships that arise among variables within the portfolio. The relationships between classification persistence, portfolio churn and net return is of particular interest. Finally, the marginal benefit of return by trading stocks based on the fundamental factor signals at the cost of incurring additional trading costs was also examined.

The ever-changing investment arena offers considerable challenges, but also significant opportunities to profit. It is the hope that this study will contribute to the current debate on smart beta. Furthermore, it is envisaged that the study will provide investment professionals with valuable insights to improve their understanding of the forces at play in a smart beta investment strategy.

The origin of smart beta and the current debate around the validity of the investment strategy will be explored in the next chapter. Thereafter, Chapter 3 will identify the research questions and objectives as well as the research methodology followed to address these objectives. The results of the study will be discussed in Chapters 4 and 5. Finally, Chapter 6 will conclude the study by discussing the primary conclusions that were established in Chapters 4 and 5 and applying these findings to challenges experienced in the South African equity market.

CHAPTER 2

SMART BETA: HOAX, 'GOLDEN EGG' OR SOMEWHERE IN-BETWEEN?

2.1 INTRODUCTION

The latest addition to investment styles in the financial arena, called 'smart beta' or 'fundamental indexing', has been noticed by many market participants. The question that arises is whether market participants truly understand the smart beta concept, and secondly, whether this investment philosophy will have longevity in the markets. Smart beta has been slow to penetrate emerging markets, and South Africa is no exception. The point at issue is why the emerging markets, including South Africa, are not pursuing this new investment philosophy. Moreover, what challenges are obstructing market participants from engaging with this new opportunity and how can these challenges be addressed (Kahn & Lemmon, 2016)?

There is sufficient literature that demonstrates the soundness of the theory behind smart beta strategies (see Fama & French, 1998, 2006; Van Heerden, 2014; Hou, Xue & Zhang, 2016). These strategies have managed to outperform their respective benchmarks throughout varying economic conditions in global markets because they are not exclusively passive in nature. Smart beta strategies are, however, passive in the sense that, once the specific fund's philosophy has been determined, the factors have been identified and each factor's requirements is set, it is merely a question of using the algorithm that trades accordingly. In this way the smart beta fund works similar to an index. However, active decision-making is involved in developing the algorithm and therefore subjectivity comes into play.

In addition, operational decisions such as the weighting-scheme and rebalancing frequency can have material effects on fund performance. It therefore becomes necessary to investigate these active, and therefore subjective, actions taken in smart beta portfolios. Since the financial market constraints of emerging economies vary considerably from their developed counterparts, the arena for such active decisions is vastly different for emerging market fund managers. The reasoning behind the lack of enthusiasm may originate from the differences experienced by emerging market fund managers. Thus, it is worthwhile to identify these differences and investigate how they present challenges and how such challenges can be negotiated. Limited research has been conducted to shed light on the active fund management involved in smart beta strategies. These decisions, however, are crucial to the fund's performance. It therefore is advantageous to market participants to understand the interrelationships that are present in a smart beta fund. This study intended to shed some light on the challenges and opportunities that arise in smart beta fund portfolio construction management.

In order to address these challenges, it is firstly necessary to gain a deeper understanding of what smart beta strategies constitute. This chapter therefore sets out to provide a thorough background of the theory and market conditions which have led to the initial smart beta strategies, and to lay a foundation to investigate the implementation of smart beta strategies and the challenges that arise in this process.

2.2 EFFICIENT MARKET HYPOTHESIS (EMH)

Theoretically speaking, markets are assumed to immediately respond to new information entering the market by adjusting prices to account for this new information. This assumption is based on the efficient market hypothesis (EMH), as described by Fama (1970). Fama (1970: 383) defines an efficient market as an ideal market where prices always fully reflect all available information, stating:

> "The primary role of the capital market is allocation of ownership of the economy's capital stock. In general terms, the ideal is a market in which prices provide accurate signals for resource allocation."

Investors therefore have the ability to select stocks knowing the current stock price reflect all available information. Similarly, firms can decide to invest in their own expansion based on this assumption. Thus, all members within this so-called 'efficient market' can make informed decisions.

Efficient markets eliminate the opportunity to earn alpha. Where alpha refers to the excess return generated by an investment, and therefore alpha acts as a risk-adjusted performance measure. Thus, a strategy's ability to earn alpha refers to its ability to outperform its market benchmark. Fama (1970) elaborates on the EMH by defining three forms of market efficiency, namely the weak-form EMH, the semi-strong form EMH and the strong- form EMH. Both the weak and semi-strong form EMH still allow for some degree of earning alpha by following an active strategy. However, within the strong-form EMH, no opportunity for earning alpha exists as markets are considered to be completely efficient. Thus, no arbitrage opportunities are supposed to exist.

The weak-form EMH assumes that stock prices follow a ‘random walk’ and cannot be predicted by studying past price patterns (Fama, 1991). Therefore, technical analysts using previous price data in order to establish patterns cannot do so successfully as all price movements are considered random. The semi-strong form EMH builds on the weak-form, while adding the assumption that prices also represent all available public information (Fama, 1991). Therefore, the semi-strong-form EMH assumes that neither technical analysts nor fundamentalists will be able to consistently earn alpha.

Finally, the strong-form EMH assumes that market prices display all public and private information available (Fama, 1991). Considering the strong-form EMH, it is not considered possible for any market participants to consistently outperform the market. Consequently, pricing theories, namely the arbitrage pricing theory (APT) and the CAPM were established in order to profit in an efficient market.

2.2.1 Asset pricing models assuming an efficient market

The CAPM as suggested by William Sharpe (1964) and John Lintner (1965) prices equities while assuming that an efficient market holds. The theory according to the CAPM is that investors should only be compensated for the risk they carry that cannot be diversified away, which is referred to as ‘systematic risk’. Thus, Sharpe (1964) and Lintner (1965) argue that any risk that investors are exposed to as a result of deviating from the so-called market portfolio (i.e. firm-specific or ‘unsystematic risk’) should not increase the expected return of the stock. Sharpe (1964) and Lintner (1965) believe that this additional risk is purely due to investor choice.

However, this line of reasoning was severely critiqued and led to the development of the APT. The premise of the APT, on the other hand, is that two assets holding equal risk should be worth the same. This assumption is known as the law of one price. Modigliani and Pogue (1988) describe the APT as a multifactor model that allows investors to identify various factors that contribute to asset returns and the sensitivity of assets to those factors. Regardless of the desirable characteristics of the APT, modern portfolio theory prefers to use the CAPM. The CAPM uses beta as a measure of systematic risk. According to the CAPM, beta is the only risk investors should be compensated for. Beta represents the extent of a movement of a specific stock in relation to the market. For instance, if a stock's beta is equal to two, the stock will roughly move twice as much as the market's risk premium over and above the risk-free rate. Similarly, if the market gains three per cent, the stock will be expected to gain six per cent if the risk-free rate is insignificantly small. High beta stocks therefore are considered to yield a high return, but also have a high risk because the possible downside is larger than that of low beta stocks. However, the CAPM only holds if the EMH holds. This prerequisite presents discrepancies when using the CAPM to price assets in the market.

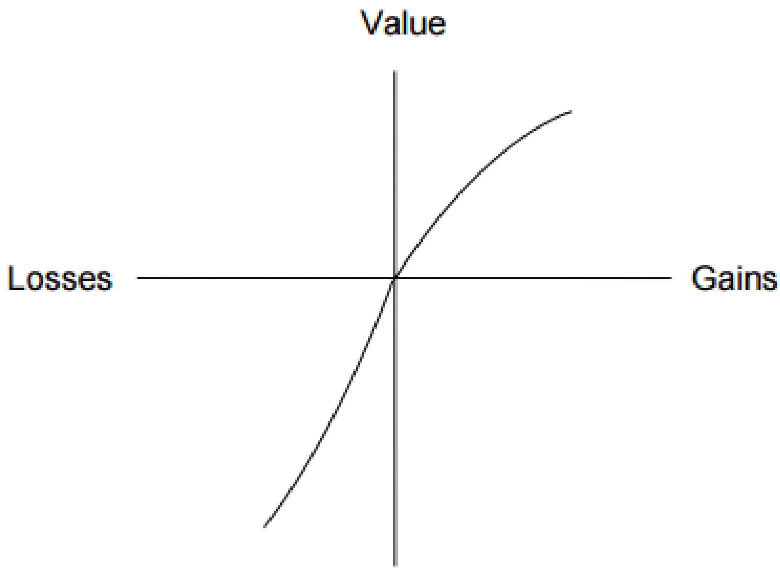
2.2.2 Behavioural biases as a counterargument for the EMH

It is evident in markets that perfect information, as suggested by the EMH, is often not available. Shostak (1997) and Malkiel (2003), amongst others, argue against the existence of an efficient market. The critique has largely been based on the existence of several behavioural biases evident in the market. 'Behavioural biases' refer to psychological reasoning displayed by market participants that cannot be logically explained. Such biases can be divided into two general categories, namely the overconfidence category and the prospect theory category (Scott, Stumpp & Xu, 2003). Kahneman and Tversky (1974) define overconfidence as an irrational belief in one's own ability to make above-average decisions by assigning a higher possibility of success to their own forecasts. The consequences of this behavioural bias are multiple as explained by Scott et al. (2003).

Firstly, investors tend to seek confirmation for their existing beliefs and tend to disregard information challenging these beliefs (Kahneman *et al*., 1974; Grether, 1980). This tendency is known as confirmation bias. Secondly, investors are slow to update their beliefs, behaviour that is defined as conservatism (Daniel, Hirschleifer & Subrahmanyam, 1998). Thirdly, extreme events may leave an impression on investors and as a result they assign an illogically high probability of such events occurring again (De Bondt & Thaler, 1985). Finally, investor conclusions are a product of how statements are framed (Kahneman & Tversky, 1984). In other words, how information is received, specifically whether it is framed positively or negatively will influence how an investor processes this information. These biases clearly challenge the EMH as these investors act irrationally. The challenge is that this irrational behaviour cannot always be predicted and therefore prices have difficulty to correctly adjust in anticipation of this irrationality.

The prospect theory (Kahneman & Tversky, 1979) is based on the utility function that is experienced by investors when incurring gains versus incurring losses. Figure 2.1 illustrates investors' diminishing marginal disutility. In other words, losses hurt more than gains satisfy.

Figure 2.1 Prospect theory utility function



Source: Kahneman and Tversky (1979: 279)

Investors' diminishing marginal disutility is in agreement with the assumption that investors are in essence risk-averse. When presented with two investment options that have the same expected returns, an investor will always choose the investment with the lowest risk. Modern portfolio theory assumes that an investor will prefer the investment offering the highest Sharpe ratio. The Sharpe ratio is a representation of the units of return offered for every new unit of risk assumed (Sharpe, 1964). Kahneman and Tversky (1979) continue to describe how investors view the original purchasing price as a point of reference and therefore make irrational decisions. This phenomenon is known as the 'disposition effect' and leads investors to hold on to losing stocks for too long while selling winning stocks too early. Investors display mental accounting by making financial decisions while mentally dividing their capital accounts (Thaler, 1985). For instance, investors are happy to spend income earned from investments but are hesitant to spend capital growth. The investors' rational reasoning would be to think of all capital investments as one account and having the same disposition to spending any of it.

Several other behavioural biases exist, but they all lead to the same conclusion. The assumption of an efficient market and correspondingly prices that always display perfect information is not necessarily possible. These biases are extremely difficult for market mechanisms to correctly adjust prices. Therefore, markets are not efficient and as such the opportunity arise to profit from these market imperfections. Van Heerden (2014) rejects the use of the CAPM model and the existence of the EMH in the South African context. Therefore, more comprehensive models that can function beyond the assumption of an efficient market are needed to price equities.

2.2.3 Bubbles as evidence of market inefficiency

Asset bubbles have been widely observed and serve as evidence of the inefficiency of markets. These bubbles are strong indicators against the efficient market hypothesis. An asset bubble was recorded as early as 1634 when the tulip mania hit the Netherlands in the 17th century. Tulip bulbs became worth exponentially more than what their fair value was. Price increases of up to 20 per cent in a single month were observed. Several investors viewed the tulip mania as an incredible opportunity to profit. Others opted to sell any assets they could manage to liquidate, including their housing and land, to acquire more bulbs. As a result, those who participated in the trend lost fortunes when the bubble burst in 1967. The market price of tulip bulbs started to plummet towards their true value. This bubble burst left the Netherlands crippled under economic depression, affecting even those who did not participate in the craze.

Another example of an asset bubble is that which led to the fall of Nortel in the 1990s. The telecommunication industry, especially Nortel, Nokia and Ericsson, experienced exponential growth during this period. This growth led to their price-to-earnings (PE) ratios nearing triple digits. Nortel managed to represent approximately one-third of the Canadian stock market while managing below four per cent in firm sales as a percentage of the national gross domestic product (GDP). As investors' expectations of future growth and correspondingly, future cash flows, increased, so did the price of the stock. Eventually, the expectations far exceeded realistic expectations of Nortel's future growth. When the firm failed to realise these excessive growth expectations, prices started to plummet. Similarly, Nokia and Ericsson were also exposed to unrealistic growth expectations. However, they managed to somewhat still satisfy investors. Their stock prices fell by approximately 80 per cent, instead of the complete devastation that saw Nortel's stock become almost worthless.

More well-known, recent asset bubbles include the technology bubble at the turn of the century and the subprime housing bubble which devastated the global economy in 2008. Both displayed similar characteristics to previous bubbles. As investors' expectations of future cash flows became unrealistically high, prices started to surge. However, at some point these bubbles will be confronted with the reality and considerable losses will always be the result of this confrontation.

Asset bubbles have the power to cripple global industry giants. As a result, fundamental analysis is clearly not the be-all and end-all of investment strategies. The inability of analysts and investors to identify such market anomalies if and when they occur, may lead to extraordinary risks and losses. Thus, financial markets cannot rationally be considered to be coherent with the EMH.

2.2.4 Market inefficiency and its consequences

A fundamental analysis in essence refers to the act of determining a stock's intrinsic value followed by trading that is based on that estimate. Due to market inefficiency and the inability of models aiming to determine the intrinsic value of considering such market anomalies, it is not possible to always accurately determine a stock's true intrinsic or fair value. In fact, if one would be able to see into the future and know all future cash flows of a firm, it would be possible to determine what the actual fair and true value of the stock should be. However, this crystal ball does not exist in reality. This "clairvoyant value", as Bill Sharpe refers to the phenomenon, cannot be determined without the benefit of hindsight. Instead, it can be seen that intrinsic values which are determined by means of fundamental analysis without the benefit of hindsight differs significantly from the true values that are determined with the benefit of hindsight, or the so-called clairvoyant value. This ‘pricing error’ clearly identifies the need for an alternative approach to investing that would eliminate the exposure to such errors from deteriorating investment portfolios.

2.3 THE RISE AND FALL OF THE CAPITALISATION-WEIGHTED INDEX

Cap-weighted indices have been widely used as a benchmark. Several active portfolio managers aim to outperform such indices by overweighting undervalued stocks (stocks that trade below their intrinsic value) and underweighting overvalued stocks (stocks that trade above their intrinsic value). However, to justify any active trading it must be assumed that markets are not efficient. Stocks are not priced at their fair or intrinsic value, but instead can be considered over- or undervalued. To assume that market cap-weighted indices are optimal passive investments and therefore using them as a benchmark, it must be assumed that markets are, at least to some extent, efficient and that investors make rational decisions. These assumptions clearly contradict one another and therefore this practice of using market cap-weighted benchmarks must be flawed. The EMH as described by Fama (1970) has been widely disregarded as unrealistic (Grossman & Stiglitz, 1980; Malkiel, 2003). To further investigate this oddity, market cap-weighted indices must first be thoroughly understood.

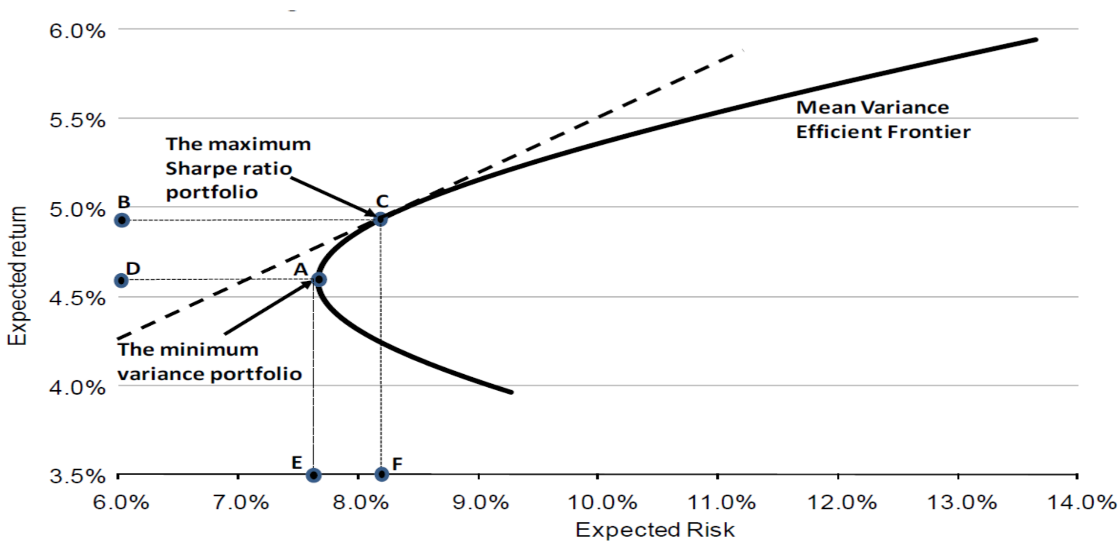
Market capitalisation-weighted, or cap-weighted, indices have been a common benchmark and index for investment professionals in the past. More specifically, investors attempting to closely track such indices passively make use of these equity portfolios that are benchmarked against market cap-weighted indices. However, these indices can be of importance to investors in actively managed funds as well. The reason for the importance of the indices is that some active funds are benchmarked against these market cap-weighted indices since the risk profile and performance of these actively managed funds are narrowly related to the indices.

Essentially these funds replicate a given segment of the market. This replication is achieved by constructing the cap-weighted index portfolio in such a way that each stock represents the same percentage of the total portfolio as that share’s market capitalisation to the market as a whole. In other words, if a TOP40 cap-weighted index should be constructed and a specific share's market capitalisation is 20 per cent of the total market capitalisation of all the TOP40 stocks combined, 20 per cent of the portfolio will be allocated to that specific share. Cap-weighted indices allow that larger firms have a bigger influence on the movement of the portfolio or index. Here, market capitalisation is defined as the number of ordinary stocks outstanding times the price per ordinary share. A larger firm will therefore have a larger market capitalisation.

The market participants who support cap-weighted indices as a relevant benchmark do so vocally and with several typical supporting arguments. Some of the notable arguments in favour of cap-weighted portfolio strategies are as follows: firstly, these strategies are passive and therefore require little to no active management which leads to lower fees. Secondly, these strategies assure that the majority of the portfolio is invested in highly liquid stocks. The increased liquidity is a result of the inherent allocation of a cap-weighted strategy as it assigns the greatest weights to larger firms. Since liquidity and market capitalisation is highly correlated, it can be expected that these strategies lead to liquid investments (Hsu, 2004). Thirdly, costs are reduced even further as these portfolios do not incur rebalancing costs considering that they are rebalanced automatically as the prices of securities vary. Finally, another key argument in support of cap-weighted indices is that it is theoretically consistent with the CAPM. Thus, a market cap-weighted portfolio should be mean variance efficient, if the market is considered efficient. Thus, the portfolio is expected to be on the efficient frontier as displayed in Figure 2.2.

Figure 2.2 demonstrates that any portfolio on the efficient frontier, such as point C in the figure, delivers the optimal return for the specific units of risk tolerated (Merton, 1972). In other words, these portfolios ensure the maximisation of the Sharpe ratio. The first three arguments are generally considered to hold within the market. However, the final beneficial argument, namely that the portfolios are mean variance efficient, only hold when very specific assumptions prevail (Hsu, 2004). Clare, Motson and Thomas (2013) challenge this conclusion that market cap-weighted funds lie on the efficient frontier. Clare *et al.* (2013) argue that investments in market cap-weighted portfolios are for convenience and low costs rather than for their theoretical consistency with the CAPM.

Figure 2.2 The efficient frontier



Source: Clare, Motson and Thomas (2013).

Given the definition of the cap-weighted index its first downfall is evident. Cap-weighted indices systematically overweight overpriced stocks (Hsu, 2004; Arnott, Hsu & West, 2008). Therefore, it increases the risk exposure to mispriced stocks. The most compelling argument against market cap-weighted indices, however, is that of Clare *et al*. (2013) who believe that monkeys would outperform fund managers using market cap-weighted funds. In this argument by Clare *et al*. (2013), 'monkeys' refer to ten million randomly chosen stocks as done by a Monte Carlo simulation in an equally weighted index. In other words, if constituent weights are chosen at random, superior risk-adjusted returns would be delivered compared to the returns that would be produced by a cap-weighted scheme (Clare *et al*., 2013).

For obvious reasons, believers in market cap-weighted investments are discontented with the study of Clare *et al*. (2013). Investors are dissatisfied with paying for a service (i.e. provided by fund managers) that they do not believe adds value. It is expected that, should investors be aware of these findings, they would take their business elsewhere. Considering that 'monkeys outperform fund managers' is such an attention-grabbing headline, the research of Clare *et al.* (2013) has captured the attention of both the media and a broader audience of investors. As a result, several investors have pursued alternative investing styles instead. This in turn, has led to investors turning their attention to smart beta strategies, amongst other investment strategies.

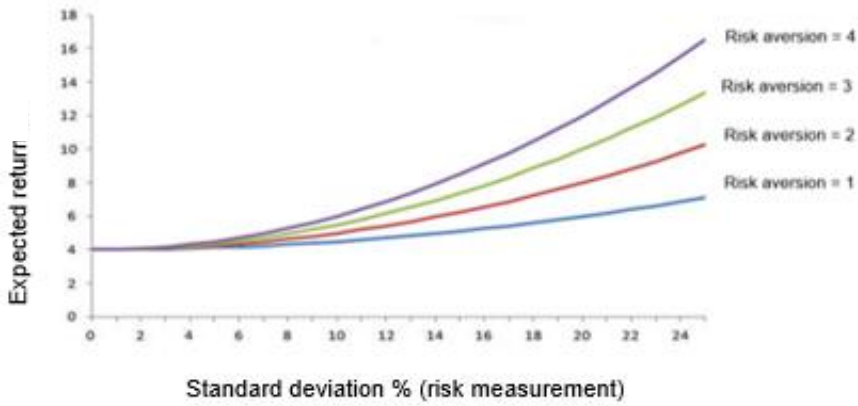
2.4 THE SMART BETA DEBATE

The smart beta investment strategy is one of the most recent additions to the international offering of investment styles. It refers to creating a semi-passive fund tracker based on a selection of fundamental factors. Such factors can include volatility, value, size, momentum and liquidity. Essentially, a smart beta fund is a semi-passive portfolio constructed by choosing stocks based on whether they meet certain requirements such as a maximum market capitalisation level. This portfolio is then only rebalanced on a predetermined periodic basis to represent the change in stocks that meet the factor requirements. A smart beta fund provides a low cost alternative to market cap-weighted indices. Smart beta funds can also provide more control over the specific risks an investor is exposed to compared to the control that a market cap-weighted index can provide. As a result, smart beta investment strategies have gained popularity in recent years as more fund managers have become informed and subsequently started implementing this alternative investment strategy (Eckett, 2016). These strategies, also known as ‘strategic beta’, ‘alternative equity beta investing’, ‘advanced beta’, ‘beta plus’ or ‘beta prime’ amongst others, have been experiencing extraordinary growth.

Smart beta denies the traditional ideas of market cap-weighted indices and has as such been widely deliberated. As a result, several arguments in favour of and against smart beta have been voiced. The smart beta investment style has notable support in prior literature. Arnott *et al*. (2008) support smart beta, referring to it as “the evolution of investment strategies”. These authors argue that the most evident benefits of smart beta investment styles include its liquidity, diversification, extensive investment capacity, cost comparison, representation of the broader market, low turnover and ease of implementation and monitoring (Arnott *et al.,* 2008).

Modern portfolio theory as described by Markowitz (1991) further explains the rationale that investors should typically be risk-averse. Therefore, investors should always prefer the portfolio with the lowest risk for a given level of expected return. This concept is illustrated in Figure 2.3.

Figure 2.3 Modern portfolio theory: Risk and return indifference curves



Author's deduction.

The risk attitude scale (0 - 6) represents an investor's attitude towards accepting risk. A risk-averse investor will score higher on the risk attitude scale, while a risk seeking investor may score as little as null on the risk attitude scale. The corresponding risk-indifference curves represent the investor's attitude towards including more risk into their profile in order to potentially realise additional returns. A positive correlation between risk and returns exist. Therefore, the more risk (higher standard deviation of returns) an investor is willing to assume, the higher the investor's possible returns. By moving to a lower indifference curve the investor assumes a lower risk aversion and increases their probability of higher returns, but also higher losses. For instance, if an investor aims to realise eight per cent return, then the investor would prefer a portfolio with the characteristics of an indifference curve with a risk-aversion of four per cent, as indicated in Figure 2.3. Stated otherwise, the investor would be willing to accept approximately 15 per cent standard deviation (as a measure of risk), rather than the approximate 17 per cent standard deviation the investor would have to endure should the investor move to the lower risk-indifference curve. The risk-aversion rating is therefore a measure of risk tolerance. The lower the rating, the more risk an investor is willing to assume. A risk-averse investor will therefore have a higher rating and lie on a higher indifference curve. A rational investor will always prefer the highest possible indifference curve for a given level of risk, therefore maximising returns for the amount of risk the investor is willing to assume.

Investors use methods of diversification to give effect to their risk-aversion by effectively decreasing the risk of the overall portfolio due to the strategic combination of assets. The ability of smart beta to expose an investor to chosen risks through means of factor selection is therefore extremely sought-after. As a result, smart beta portfolio construction has been described as a means of managing risks rather that managing return and as a result achieving the desired return. This is because of the law of investing, i.e. increased return equals more risk. An investor cannot realise return without assuming some extent of risk. By focusing on risk management, investors can realise return while ensuring they remain within their required maximum risk constraints. Smart beta can be seen as a new financial instrument to effectively diversify. As a result, investors who are drawn to the more passive, lower-risk investment products on the market will be the expected target audience for smart beta funds.

2.4.1 Both sides of the pendulum

As with most new ideas there will be those in support and those who critique. Whenever smart beta is mentioned, Arnott *et al*. (2008) should be considered. As the authors of *The fundamental index: A better way to invest*, they introduced many market participants to the concept of smart beta. However, not everyone agreed with their favourable outlook on the prospect of smart beta. Philips, Kinniry, Walker and Thomas (2011) claim that Arnott *et al.* (2008) are misguided in their support of these funds. Philips *et al*. (2011) argue that smart beta funds actualise a systematically inherent beta exposure towards value and smaller-cap stocks within the targeted benchmark. They furthermore demonstrate that smart beta funds, after accounting for style and size exposures, do not generate alpha (Philips *et al.,* 2011). Although some support smart beta for its ease of implementation and cost comparison, Cox (2014) believes that these funds lack transparency. Smart beta funds have come into dispute due to a lack of a proven track record as they are relatively new to the market. Instead, smart beta funds rely on backtesting in comparison to actively managed funds, which are marketed on the basis of their established track record (Cox, 2014).

In *The fundamental index: A better way to invest,* Arnott *et al*. (2008: 151-185) note the criticism that smart beta funds typically endure. The questions and debates come from several dignitaries in the financial sector, such as Burton Malkiel, a Princeton professor; Jack Bogle, author of *A Random Walk Down Wall Street;* Andre Perold, a Harvard Business School professor; and Cliff Asness, a prominent hedge fund manager. Their main criticism is that smart beta strategies are merely a value tilt. Smart beta investment styles, according to these dignitaries, have a structural value tilt in comparison to a cap-weighted market. This structural value tilt refers to a value premium being demanded as stocks with low price-to-book ratios and high dividend yields have proven to outperform over long periods. Arnott *et al*. (2008), however, demonstrate that in an efficient market, no disadvantage will be borne by a smart beta portfolio because of its value bias relative to the cap-weighted market. Since the market prices growth firms at a premium and value firms at a discount, smart beta simply neutralises the growth bets that the market is making at the time (Arnott *et al.* 2008). The growth bets are effectively neutralised by adjusting the weights of stocks within the investment horizon back to the economic scale of the firms. A growth bias is present within market cap-weighted strategies, while a value bias is noted in smart beta strategies. The value bias, however, does not lead to a disadvantage in comparison to market cap-weighted strategies. By effectively neutralising the growth bias, smart beta strategies deliver superior performance relative to market cap-weighted strategies.

A smart beta strategy will effectively trade against all the extreme bets, be it growth or value. As a result of factors moving slower than stock prices as demonstrated by Shiller (1981), the majority of these trades will prove to be profitable. Subsequently, Arnott *et al.* (2008) believe a smart beta portfolio adds up to four times as much value relative to a tracking error of a cap-weighted simple value portfolio. This argument is in contrast with Philips *et al*. (2011), who believe an investor would be better off with such a cap-weighted focused portfolio.

2.5 THE IDEA OF SMART BETA INDEXING GETS ROOTS

Behavioural biases create a market where there is opportunity to profit from market anomalies. These anomalies, such as the size effect (Banz, 1981; Berk, 1995), are well-documented in the extant literature. Fama and French (1998) realise that an opportunity to profit from such irregularities exists, if understood correctly. This realisation led to the development of the Fama and French three-factor asset pricing model (Fama & French, 1998), and later their extended five-factor model (Fama & French, 2014).

2.5.1 Fama and French three-factor model

The initial three-factor model was developed to expand on the CAPM of William Sharpe (1964) and John Lintner (1965), which only considers market risk in terms of beta. Fama and French expanded the CAPM to incorporate two more factors, namely value (called high-minus-low) and size (called small-minus-big). Their reasoning was that empirical evidence has shown that the existence of a size factor where stocks with smaller market capitalisations will outperform those with larger market capitalisations (Banz, 1981; Berk, 1995). Value stocks are considered to outperform growth stocks (Dreman, 1979). The assertion is that value stocks carry greater risk than growth stocks and therefore investors demand higher returns as compensation for assuming additional risk. Because investors can profit from such characteristics, Fama and French (1993) argue that these three factors should be considered when determining expected return.

2.5.1.1 Market factor

The market factor is represented by using the CAPM, or more specifically, beta. As explained earlier in this chapter, beta is a measure of systematic risk. Systematic risk refers to the risks that cannot be diversified away as they are imminent within the market as a whole. Thus, beta acts as a measure of the sensitivity of an asset to market movements.

2.5.1.2 Size factor

The size factor or small-capitalisation bias refers to the market anomaly that smaller firms, based on market capitalisation, generate higher returns on average than their larger counterparts (Banz, 1981). This anomaly is a result of the fundamental idea that riskier cash flows should be discounted at higher rates. When determining future cash flows, smaller firms are inherently riskier and their cash flows will therefore be discounted at higher rates. This inherent risk is because small firms are less resilient to withstand periods of economic downturn and are generally less liquid than their larger counterparts (Arnott *et al*., 2008: 161). When comparing a small firm with a larger counterpart that has the same cash flows, the intrinsic value, or present value of future cash flows, will be lower for the small firm. According to the risk return trade-off, in order to acquire additional return, one must assume additional risk. This trade-off, however, always comes with a possible downside too as stocks with a higher risk, and therefore higher possible returns, also have a higher probability of performing poorly. A higher growth rate can be expected for the smaller firms than for larger firms when market movements are favourable. Small market capitalisation firms therefore offer a means of acquiring additional expected return by assuming additional risk.

2.5.1.3 Value factor

The value factor aims to profit on the value premium which is evident in the market. Ample previous academic research has identified the existence of such a premium where stocks with high dividend yields and low price-to-book ratios tend to outperform in the long term. Fama and French (1993) initially displayed this premium by making use of the high-minus-low (HML) concept. This concept is used to measure equity returns based on valuation by taking high price-to-book ratios and subtracting low price-to-book ratios.

The value factor demonstrates that value stocks tend to outperform growth stocks. However, the existence and profitability of a value premium has been debated in literature and practice for decades. Fama and French (1998) demonstrated what they considered to be evidence of this value premium. By analysing performance of value and growth stocks in 13 stock markets, they concluded that a value premium was indeed evident for the period 1975 to 1995 as 12 of the 13 stock markets exhibited value stocks outperforming the growth stocks. In addition, Zhang (2005) confirms how this value anomaly, which is generally considered because of investor irrationality (DeBondt & Thaler, 1985; Lakonishok, Shleifer & Vishny, 1994), is consistent with the rational expectations of investors.

Phalippou (2004) disregards the value premium as a worthy factor to consider even though he concedes that it does exist. He contends that the value premium is extremely concentrated to approximately seven per cent of the stock market. He continues to argue that the value effect is largely observed only within stocks held by individual investors, while the value premium observed within institutional ownership is unremarkably small. As a result, Phalippou advises market participants to disregard the value premium and considers the stock market to be value anomaly free for the most part. Hougе and Loghran (2006) furthermore concede to the lack of a value premium being evident within the market to the extent that investors can expect to profit from this premium. They also link the existence of any value premium that is present to only be observed for smaller stocks. However, this claim that larger stocks do not experience a value premium is disputed by Fama and French (2006).

Fama and French (2006) demonstrated that when the existence of a value premium is measured by earnings yield multiples, rather than book-to-market as used to disprove a value premium, a value factor is present regardless of firm size. A value premium is more evident outside the US while most studies have focused on disproving a premium in the US equity market (Fama & French, 2006). It therefore seems that the value factor is evident within global equity markets and that the critique is largely based on aberrations where the value premium wavers for a period of time.

The continuous debate around the Fama and French three-factor model has yet to disprove its viability. The three-factor model is still used widely in most fundamental analysts' processes of determining the intrinsic value of stocks. Still, Fama and French (2014) saw an opportunity to further enhance their model to identify two new factors that are prevalent in the market.

2.5.2 Fama and French five-factor model

Fama and French (2014) expanded the three-factor model to consider five factors. They included the profitability and investment factors. The profitability factor is based on the concept that firms with higher expected future earnings should theoretically realise higher market returns. This concept is derived from the dividend discount model (Gordan, 1959) which states that a stock's present value is the sum of its discounted future cash flows. The challenge, however, lies in finding a model to accurately estimate future cash flows. The profitability ratio is seen as such a model and therefore is the basis of including the fourth factor.

2.5.2.1 Profitability factor

Profitability is typically applied by studying a firm's ROE (Amenc *et al.,* 2015). Higher ROE ratios are considered evident of increased, and therefore more desirable, levels of profitability. The profitability factor aims to generate excess returns similar to that of a value strategy. A value strategy attempts to acquire productive capacity inexpensively by (short) selling overvalued assets in order to finance the acquisition of undervalued assets. Similarly, a profitability strategy finances the acquisition of productive assets through the sale of unproductive assets. In this way both these factors can generate substantial abnormal returns.

Profitable firms outperform their unprofitable counterparts in terms of average revenue despite typically having lower book-to-market ratios and higher market capitalisation. This strategy therefore seems to be negatively correlated with a value strategy as demonstrated by Novy-Marx (2013). By combining these strategies, Novy-Marx show how value investors can capitalise on the return of the profitability factor without assuming any additional risk. That is, the portfolio's exposure to risky assets will increase while the overall portfolio volatility is reduced. Therefore, the profitability factor performs exceptionally well in the context of the Fama-French five-factor model.

2.5.2.2 Investment factor

Finally, the fifth factor considered in the new five-factor model of Fama and French (2014) is investment. This investment factor studies corporate financing decisions and managers' behavioural biases. Large capital investments into projects are considered a warning sign as Titman, Wei and Xie (2004) argue that such firms are likely to subsequently realise inferior returns. Corporate finance literature warns against managers who build empires and in the process destroy capital instead of growing the firm.

According to Fama and French's (2014) five-factor model, a market participant should be able to generate the highest expected returns from investing in a small, value firm with a high ROE profitability ratio and no capital extensive projects on the horizon. In addition to the five-factors of Fama and French, smart beta fund managers have considered to include factors such as liquidity and momentum as part of their criteria for stock selection (Amenc, *et. al.,* 2015). This abundance of investment criteria leaves investors with a myriad of portfolio allocation options. However, the interest lies in those strategies with the ability to generate sufficient returns in accordance with a fund's mandate.

2.5.3 Further fundamental factors to consider

Van Heerden (2014) discusses a variety of possible factors to consider in the South African context. Such factors include liquidity (as measured by daily trading volume), momentum, age, price-to-book value, low risk, stock buybacks and management ownership. An extensive list of possible factors to consider are provided in Annexure A. Annexure B also provides further insight into smart beta strategies and the underlying factors as an aid to the reader. However, recent research by Morgan Stanley Capital International (MSCI) suggests that value, size, high yield, low volatility, quality and momentum are the only factors that have an adequate grounding in academic research. These factors also offer comprehensive explanations of how and why they historically produced alphas (Bender, Briand, Melas & Subramanian, 2013). The remaining factors that have not been discussed, namely, momentum, high yield, low volatility and quality will be examined in the following sections.

2.5.3.1 Momentum factor

Jagadeesh and Titman (1993) found that a strategy of buying stocks that have performed well in the past and selling stocks that have performed poorly in the past offers outperformance. These positive returns are, however, only realised over the short term, specifically three to twelve months, after which mean reversion dissipates the excess returns.

Van Heerden (2014) identifies significant value (as measured by cash-flow-to-price and book-value-to-market-value) and momentum (as measured by twelve- month prior returns) effects that are present in the South African investment environment. However, the momentum effect disappears when the markets lack depth. Market depth refers to the ability of a market to execute relatively large orders without causing price discovery. Thus, market depth is a representation of the number of open orders within a specific security. The value effect, on the other hand, seems to be more robust as it remains significant within varying levels of liquidity that is present in markets. Both value and momentum are insensitive to time, while the size effect (as best measured by the market capitalisation value) suggested by Van Heerden (2014), is sensitive to time and liquidity. Once the pay-off period is extended from one month, the momentum effect becomes less significant while the size effect becomes more significant.

Van Heerden's findings are supported by Beck, Hsu, Kalesnik and Kostka (2016), who conclude that factors can be divided into two groups, namely more liquidity demanding factors and less liquidity demanding factors. They group momentum and illiquidity into the liquidity demanding group, while value and low beta still hold without significant liquidity levels present. Beck *et al*. (2016) furthermore suggest that skilled active managers with competitive pricing structures might be more suited to pursue factors in the more liquidity demanding group. However, indexation built upon factors in the less liquidity demanding group remains the optimal low cost option to gain exposure to these factors (Beck *et al*., 2016).

2.5.3.2 High yield (dividend) factor

The high yield or dividend factor captures excess returns generated by firms who offer above-average high dividend yields. Whenever a firm changes its dividend, which leads to a change in its dividend yield, it is to be expected that this change in the dividend will have an influence on its stock price. The belief is that market participants will speculate on the prospects that a change in dividend yield might suggest in terms of future earnings. For instance, a positive (upward) change in the dividend yield can lead investors to believe that this change suggests increased returns for a firm in the future. However, Black and Scholes (1974) assert that this change is more often than not merely a temporary change. Investors are bound to realise that the change in the dividend yield does not reflect any real long-term change in returns. As a result, the stock price will begin moving back to its pre-dividend yield change levels. The high yield factor present due to investor perceptions therefore only generates excess returns in the short term.

Graham and Dodd (1951) suggest a different approach to explain this high yield premium. They believe that shareholders prefer that a dollar is paid to them by means of a dividend to a dollar in capital gains. The certainty of receiving the payout rather than the promise of future possible financial gains is more attractive to shareholders. As a result, investors will bid up the stock price of high yielding firms as compared to their counterparts that pay lower dividends (Graham & Dodd, 1951). No matter what the reasoning is behind the existence of a high yield premium, it is evident in the market and has been extensively debated in academic literature. Therefore, high yield will remain a factor to consider.

2.5.3.3 Low volatility factor

Volatility is seen as a measure of risk in the stock market. High volatility stocks are considered to have higher risk indebted within that investment than their lower volatility counterparts. The risk-return trade-off, which is accepted as a law in the asset management arena, states that in order to generate additional return, the investor must assume additional risk. The practice of diversification offers relief from this law and therefore acts as a risk management technique. Diversification is the practice of combining a wide variety of assets into a single portfolio. A diversified portfolio is expected to yield higher risk-adjusted returns by incurring lower risk (volatility) than any single investment, on average, yields.

Traditional finance assumes investors to be risk-averse. Investors are therefore expected to act rationally and as a result, prefer investments with the highest return for a given level of risk. This level of risk is determined by investor preference and capacity. In other words, investors are expected to prefer the highest Sharpe ratio attainable.

The low-volatility effect as explained by Clarke, de Silva and Thorley (2006) and Blitz and Van Vliet (2007) refers to the pursuit of lower risk without realising lower return. These authors studied the risk-adjusted returns of both high- and low-volatility stocks. A clear-volatility effect is evident in the study of Blitz and Van Vliet (2007) as they found that low-risk (volatility) stocks considerably outperform the market portfolio on a risk-adjusted basis. In comparison, high-risk (volatility) stocks considerably underperform the market portfolio on a risk-adjusted basis. Assuming traditional finance is correct and investors are therefore rational, they should prefer low-volatility stocks as they outperform higher volatility stocks on a risk-adjusted basis.

In summary, low volatility as a factor within a smart beta portfolio aims to profit from investing in stocks with lower volatility. In other words, the objective is to profit from the risk-adjusted outperformance of such low-volatility stocks (Blitz & Van Vliet, 2007).

2.5.3.4 Liquidity factor

Illiquid stock markets are expected to realise higher future returns than their liquid counterparts (Pástor & Stambaugh, 2003). A premium thus exists as investors demand higher returns for being exposed to additional risk. The additional risk referred to here is that of illiquidity. In other words, it denotes the risk that an investor will be unable to liquidate (sell) the asset in a timely manner should the need arise. Illiquid assets therefore carry the risk of limiting an investor's options as it becomes extremely challenging to sell such assets without incurring large costs.

Pástor and Stambaugh (2003) consider the liquidity factor to hold when it is adjusted for exposure to size, momentum and value factors as well as market return. Acharya and Pedersen (2003) support this belief that a liquidity factor is present in the financial markets. They suggest that investors should at all times take the illiquidity premium into account as the tradability of an asset can severely impair the value of an asset. However, as with any risk incurred, this additional risk also creates an opportunity for higher returns should the investor be willing and capable of assume such risk.

Avramov and Chordia (2006) expanded on the findings on liquidity of Pástor and Stambaugh (2003) by studying the impact of the level of liquidity on returns. Previous research has instead focused on capturing the impact of liquidity risk. As a result, a liquidity factor, or stated otherwise, the impact of liquidity on returns, is demonstrated to not taper off when controlling for possible business-cycle effects (Avramov & Chordia, 2006). The illiquidity premium is speculated to be a factor independent of the state of the economy and rather a result of market design. The liquidity fundamental factor holds throughout business cycles and is therefore considered to be non-cyclical (Avramov & Chordia, 2006). Siu (2015) confirms the statistically significant existence of an illiquidity premium. He demonstrates this positive relationship between absolute and risk-adjusted performance and illiquidity (Siu, 2015). Here, illiquidity is measured as weighted average days-to-trade. The more days-to-trade, the less liquid the stock. It can therefore be assumed that an illiquidity premium is evident in the market and therefore the liquidity factor offers possible outperformance opportunities.

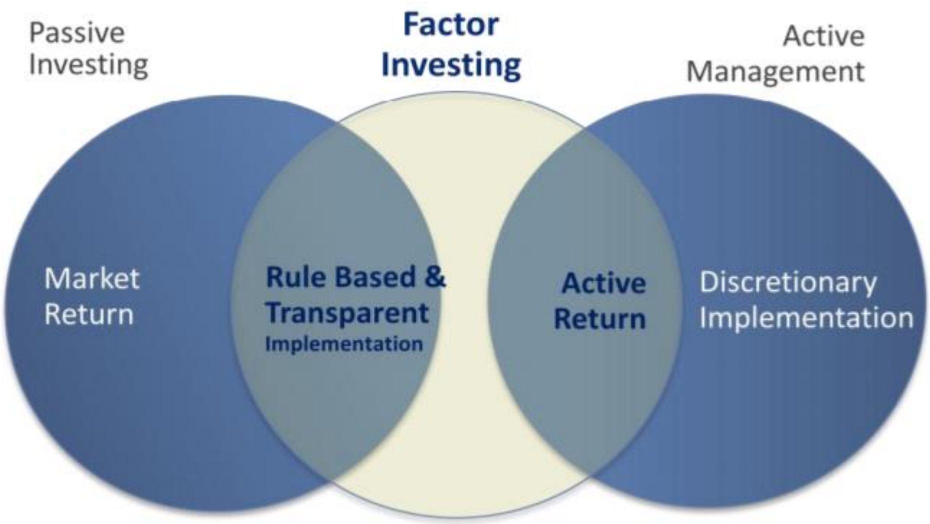
Favouring illiquid stocks present a possible challenge to smart beta fund managers. As a result of the illiquidity, should investors in the fund wish to withdraw their funds they might not be able to do so in a timely manner. Such portfolios can require up to several months of trading for an investor to completely liquidise their position in the fund. Siu (2015) suggests requiring the portfolio to meet a liquidity weighted-average yardstick. He stipulates that the simulated smart beta portfolio's weighted average days-to-trade for the given stocks should not exceed the maximum as represented by the weighted average days-to-trade of those same stocks when held at benchmark weights. Thus, by subjecting this requirement to a variable multiple, Y, he ensures that on average, the stock holdings are no less liquid than its corresponding holding in the benchmark.

In summary, an illiquidity premium is considered to be present in financial markets. Higher returns are therefore expected for investments in less liquid assets. A portfolio can be constructed to benefit from this liquidity factor. Such a portfolio will therefore favour illiquid stocks. This liquidity strategy can be executed by ‘going long’ or buying the favoured, less liquid stocks, and ‘going short’ or selling the more liquid stocks. However, the level of risk associated with such an investment can be a limiting factor to some investors and therefore an investment mandate becomes crucial.

2.5.4 Concluding remarks on fundamental factors

Even though they are considered passive, smart beta portfolios do have an active aspect to them. The active, and therefore subjective, aspect is the initial decision of which factors to include in the portfolio and which requirements each factor should be subject to. Furthermore, operational decisions such as a weighting scheme and rebalancing frequency should be considered. Once these decisions are made and the algorithm has been developed to run with these decisions, a smart beta portfolio becomes passive. Identifying the optimal factors and subsequent requirements for each is therefore vital in determining the success of the smart beta portfolio. Figure 2.4 illustrates the characteristics of both active and passive management that is related to smart beta strategies.

Figure 2.4 Smart beta drawing characteristics from active and passive strategies



Source: BlackRock, 2017.

A smart beta portfolio profits from managing its risk exposure in the form of several factors. Since each factor essentially derives its performance from a certain risk exposure, it becomes imperative to understand each risk and managing it accordingly. It becomes clear why smart beta strategies are considered to focus on managing beta (risk) instead of pursuing alpha.

Table 2.1 summarises the information on the specific factors as discussed in this chapter.

Table 2.1 Summary of fundamental factors discussed in this chapter

Factor	Factor signal relationship with best returns*	Measurement**
Market	Higher	Beta
Size	Smaller	Market capitalisation
Value	Lower	Price-to-book ratio (HML)
Profitability	Higher	Return on equity (ROE)
Investment	Less capital extensive projects	Change in total assets

Factor (cont.)	Factor signal relationship with best returns* (cont.)	Measurement** (cont.)
Momentum	Lower past one-year return → lower expected three-month return	12-month prior returns
High yield (dividend)	Higher	Dividend yield
Liquidity	Lower	Stock turnover days-to-trade
Volatility	lower	Past three-year volatility of weekly returns

Note A: * Positive relationship displayed between inscriptions in the second column and returns and/or stock performance. Thus, the inscription in the second column of the measurement of the factor (third column) will offer superior returns.
Note B: ** Measurement used to identify winner and loser stocks.

South African research suggests that the focus should be on the value effect, followed by the momentum and size effect. Value seems to be the only robust factor in the South African context as it proves to be insensitive to fluctuating variables, specifically the pay-off period, market depth and time (Van Heerden, 2014). Adversely, Van Heerden argues that the significance associated with all the other factors considered was found to be a function of one or more of time, liquidity and/or the pay-off period. The present study considers Van Heerden's (2014) findings, but it also considers all the factors listed in Table 2.1 on their own merit according to the factor requirements set for this study.

In order for this study to use a factor in the simulated smart beta portfolio, it must meet the following three requirements. Firstly, the factor must be confirmed by extensive prior academic studies. Secondly, how the factor manages to identify outperforming stocks must be understood, and finally, the data must be available within the scope of this study. The factors as discussed in this chapter meet the first two requirements. The availability of data was, however, a deciding factor as discussed in the following chapter.

2.5.5 Smart beta in practice: Can it perform?

Since very few smart beta portfolios have been in the market long enough to test their actual past performance, most market participants considering smart beta rely on backtesting. 'Backtesting' refers to the act of testing an investment strategy with actual past market data without investing any capital. True market data is used to determine how such a strategy would have performed. Backtesting, however, is subject to certain limitations. The period of backtesting, for instance, should be sufficient to include varying market conditions. Furthermore, backtesting should aim at replicating reality as accurately as possible. Trading costs and a realistic sample size should be taken into account. Many new smart beta investment options have entered the market on the back of encouraging backtesting results. Investors should therefore be informed on the validity of such backtesting results before entering into these portfolios. As no strategy will outperform in all possible market conditions, an investor should understand and support its underlying philosophy. This process of choosing a smart beta portfolio is similar to that of choosing an actively managed mutual fund.

As mentioned earlier, smart beta is an umbrella term for an extensive array of strategies that are all considered to be smart beta. These strategies, however, can vary so drastically that it becomes challenging to determine whether the umbrella term of smart beta delivers outperformance. It becomes necessary to instead ascertain whether the factors employed by the smart beta strategies have performed. Difficulties arise again as several factors are included in each smart beta portfolio at varying weights. For instance, if value underperformed, but liquidity outperformed, and both are included in one portfolio, the resultant portfolio out- or underperformance will be a question of the weights of each factor.

2.5.5.1 Accounting for costs and taxes

Another deciding factor when discussing performance is the influence of trading costs and taxes. The rebalancing period chosen for a smart beta portfolio can have a material effect. A shorter rebalancing period, thus trading more often, will increase the trading costs incurred and therefore decrease after-cost performance. Additionally, trading costs vary according to market depth. Deeper markets with more active participants can execute larger trades cheaper and with significantly more ease than markets that lack depth. The emerging South African financial markets certainly cannot be compared to those of global market leaders, such as America, Germany and Britain, in terms of market depth. It is therefore to be expected that any trade conducted in the South African equity market costs substantially more than a similar trade would cost in the US. This rebalancing period trade-off which arises is a crucial uncertainty in the study. As a result, this trade-off will be discussed in the following chapters.

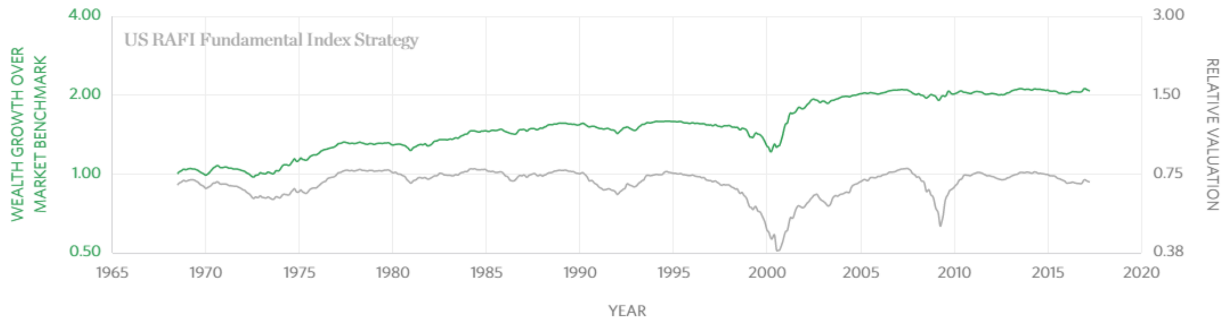
Vadlamudi and Bouchey (2014) explore the tax implications of smart beta investing. A material difference can arise as smart beta portfolios are more likely to incur capital gains than a cap-weighted index. The capital gains tax implications can adversely influence taxable investors. Building on the research of Jeffrey and Arnott (1994) and Arnott, Berkin and Ye (2001), who argue that actively managed funds' alphas cannot justify their tax bill, the research into smart beta's ability to do so has been called into question. However, Vadlamudi and Bouchey (2014) still believe that smart beta investments offer value after tax. They argue that smart beta's performance, unlike that of actively managed funds, can support their tax bill. They believe that smart beta is an ideal tool for tax management techniques. When compared to actively managed funds, smart beta funds have a lower turnover, greater diversification and breadth (Vadlamudi & Bouchey, 2014). These are all sound characteristics when implementing tax management techniques. Vadlamudi and Bouchey (2014) suggest using one, or a combination of the following tax management techniques. Firstly, deferring the realisation of gains; secondly, managing the holding period; thirdly, harvesting losses; fourthly, paying attention to tax losses and finally, avoiding wash sales. The authors demonstrate how implementing these tax management techniques with smart beta portfolios prove to be exceptionally effective.

2.5.5.2 Backtesting performance

Even when taking into account these challenges, smart beta seems to have performed encouragingly. For instance, Guggenheim, one of the pioneers of implementing strategies similar to smart beta, managed to outperform the S&P 500 by 7.4 per cent on average over a ten-year period starting in 2003 (Kapadia, 2014). This fund equal-weights its constituents and therefore increased the small stocks included with the ETFs. The Guggenheim S&P 500 Equal Weight ETF fund managed to return an average of 9.2 per cent over the same ten-year period (Kapadia, 2014). Past performance, however, does not equal future performance and therefore investors cannot expect consistent outperformance. Depending on current market conditions, the performance can worsen, especially since smart beta strategies tend to incorporate more risk than indexing.

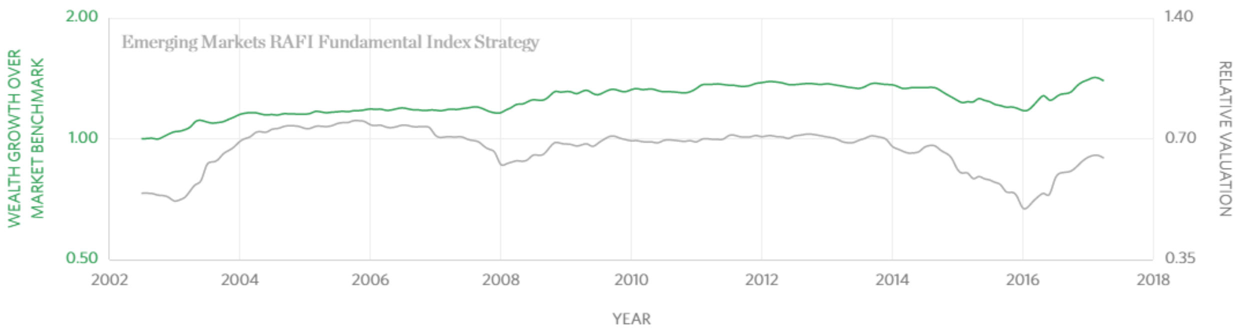
It is nonetheless worthwhile to study past performance as compared to a relevant benchmark in order to validate the research o smart beta. For this purpose, the Research Affiliates smart beta strategy, or the RAFI fundamental index, was studied as it is one of the most extensive datasets on the subject (also see Arnott *et al.,* 2008). Figures 2.5 and 2.6 in combination with Annexure C demonstrate the outperformance of the US RAFI fundamental index, which is classified as a smart beta strategy.

Figure 2.5 RAFI fundamental benchmark outperformance in the US market (net of transaction costs)



Source: Research Affiliates, 2017

Figure 2.6 RAFI fundamental benchmark outperformance in emerging markets (net of transaction costs)



Source: Research Affiliates, 2017

The US RAFI fundamental index managed to outperform its benchmark, the Russel 3000 by an average of 1.49 per cent net of trading costs over a period of 62 years. The more recent emerging market fundamental strategy developed by Research Affiliates also managed to outperform its benchmark. The extensive research period is reassuring as market conditions varied considerably across this time period and yet smart beta strategies managed to achieve outperformance.

The primary aim of this study was not to prove the validity of smart beta performance, but instead to examine the trade-offs in the active side of smart beta fund management and how these trade-offs contribute to the fund's success or failure. In order to study the contribution to performance of these trade-offs, the validity of smart beta investment strategies should first be established. The aforementioned discussion therefore aimed to remove any doubt the reader may have had towards the legitimacy of smart beta strategies. The notion of smart beta investing is considered profitable, even after taxes and costs, if it is implemented correctly. The ideal rebalancing period for a market that lacks depth is, however, yet to be determined. This study will therefore discuss this trade-off in the following chapters.

2.6 IMPLEMENTING SMART BETA

The discussion of smart beta may now continue on the intended path of this study, by considering the active decisions that are made within a smart beta portfolio. The question at hand is how to construct a smart beta portfolio, or simulated portfolio for the purposes of this study, and how to benefit from the chosen factors' premiums. Once the chosen factors have been identified, three other important aspects remain. Firstly, the stock universe that will be used must be identified; secondly, the weighting scheme decided on and finally, the rebalancing frequency chosen. These aspects will all be addressed in Chapters 4 and 5 as the simulated portfolio is built.

Davis (2015) explores the possibilities that the new phenomenon of big data bring to smart beta. 'Big data' refers to the vast amounts of data generated online whether that be through social media, product searches, merchant location searches or mobile applications, to mention a few. These vast amounts of data are captured and can reveal consumer interests or sentiments. As a result, investment professionals have noted the value of big data and some have started trading accordingly. Davis (2015) suggests that big data could be applied to the weighting scheme of smart beta portfolios in order to take consumer sentiment into account. Although it is beyond the scope of this study and the data could be difficult to obtain, it is an interesting development in smart beta and calls for further research.

2.6.1 Challenges

The decisions made with the initial implementation of a smart beta portfolio can cause challenges once the portfolio is active. A prime example is the liquidity factor. Implementing the liquidity factor, or attempting to benefit from an illiquidity premium, will necessarily decrease the ease and speed at which capital can be withdrawn from the portfolio. Other aspects that can be influenced include investability, returns, risk and tracking error. Thus, it is crucial to consider all these aspects when setting up a smart beta portfolio and deciding which factors investors may find vital to remain uncompromised.

As discussed in previous sections, taxes and other costs can be challenging as they present a danger to achieve the desired returns. However, as pointed out by Vadlamudi and Bouchey (2014), there are several tax management techniques available to reduce the threat to performance that is caused by taxes. By altering the rebalancing period costs can be managed.

2.6.2 Performance persistence

In a fund management context, performance persistence is the study of a fund's individual performance momentum and also the outperformance of a fund relative to other similar funds over time. If a fund delivers excellent returns in a particular year, one may ask what the probability is of the fund producing above average returns in the following year, or the tendency to outperform other similar funds if it has been outperforming these funds in prior periods. Alternatively, if a fund delivers exceptionally poor returns in a particular year, what would the probability be of repeating such poor returns in the subsequent year? Evidence of this phenomenon supports the conventional idea that the track record of a fund manager offers insight into their ability to manage funds. Most financial professionals will, however, warn against this reasoning as past performance is not necessarily indicative of future performance.

An abundance of research supports the notion of performance persistence, and demonstrates that the relative performance of equity mutual funds persists from period to period. Initially, Carlson (1970) noted that funds that delivered above-median returns in the preceding year would typically repeat this superior performance in the subsequent periods. Lehmann and Modest (1987), Elton and Gruher (1989), and Grinblatt and Titman (1994) support the notion of performance persistence being present within the mutual fund arena. Other authors, such as Brown and Goetzmann (1995), Elton, Gruber and Blake (1996), and Bollen and Busse (2005), illustrate a level of predictability in fund performance, hinting towards the existence of performance persistence. Loon (2010) further adjusts for model uncertainty not accounted for in prior research and found significant results of performance persistence visible in several US equity funds. Thus, substantial evidence supports the existence of performance persistence. The study at hand builds on this existing knowledge by investigating the classification persistence of stocks within the simulated smart beta fund. Accordingly, classification persistence refers to the probability of stocks to remain within the smart beta portfolio given that certain requirements, based on the chosen factors, are met so that the stocks remain within the portfolio. Essentially, classification persistence is extending the idea of performance persistence as described above within a smart beta environment. The probability of a stock to consistently meet the smart beta fundamental factor set requirements is therefore called into question.

2.6.3 Influence of trading costs

It is well-documented in the literature that active strategies have difficulty to outperform passive strategies in the long term due to trading costs. Barber and Odean (2000, 2001) estimate that the average investor in the US incurs a loss of two percentage points annually due to trading costs. Similarly, Barber, Lee, Liu and Odean (2008) reported that the estimated average loss to a Taiwanese investor was 3.8 percentage points for the same reason. Investors should logically start contemplating whether the trading associated with active portfolio management strategies are worth the costs. A trade-off forms between i) gaining exposure to a profitable opportunity not currently held in the portfolio and ii) liquidating an unprofitable stock that is currently held and incurring high costs due to frequently trading based on new information.

Smart beta funds have managed to outperform their benchmark net of trading costs as illustrated earlier in this chapter. Nonetheless, it is important to note that the performance statistics are those of smart beta investments in developed and therefore deeper markets. The lack of depth in the South African market necessarily leads to trades being more expensive to execute. A similar rebalancing frequency in a developing country such as South Africa will therefore incur much higher costs compared to a developed economy such as the US. This study attempted to examine this trade-off, especially in the South African smart beta context, and consequently suggests optimal trading schedules.

2.7 CONCLUSION

Smart beta offers promising opportunities to those who truly understand it. However, as with any investment strategy, it comes with challenges, particularly in the emerging market arena such as South Africa. However, if managed wisely, there seems to be value hidden in this new investment philosophy.

Smart beta funds do not attempt to generate alpha, unlike actively managed portfolios. Smart beta funds aim to generate sufficient returns from their selected levels of exposure to risks, thus generating beta. Market participants therefore have an interest in understanding these funds as they offer low cost alternatives, especially when compared to actively managed funds, to generate the required returns (Amenc *et al.,* 2015). Therefore, this study aimed to investigate the notion of smart beta funds and the impact of choosing different factor combinations on its return-generating ability. Furthermore, any investor is concerned with the costs of implementing a strategy as this can have a substantial negative effect on the net returns an investor achieves. Thus, the persistence of stocks being classified in a certain fundamental factor and the resultant portfolio churn (stock turnover due to stocks failing to consistently meet the factor requirements of such smart beta portfolios), were investigated.

To conclude, the aim of this study is to assist investment professionals and interested market participants to understand smart beta factor selection more comprehensively. The focus is on portfolio persistence and churn due to stocks failing to consistently meet the factor requirements. In addition, the effects of transactions arising due to stocks becoming eligible or failing to meet the requirements for another subsequent month were investigated. The influence of the chosen fundamental factor combinations in the study were assessed throughout. As a result, the research questions will be answered on the premise of different factor combinations. In this manner, the study also aims to investigate the influence of choosing different factor requirement combinations on its ability to deliver on its low cost promise while still outperforming cap-weighted indices. Market participants can benefit from such research as it will help them to further understand smart beta and to evaluate its claim to be a true low cost investment strategy. Against this background, a study of the building blocks of smart beta funds was deemed justified. Chapter 3 discusses how the study addressed each respective research objective.

CHAPTER 3

RESEARCH DESIGN AND METHODOLOGY

3.1 INTRODUCTION

As highlighted in Chapters 1 and 2, smart beta has become a popular investment philosophy internationally. However, as an emerging economy, South Africa has been slower to adjust to and implement this new investment strategy compared to its developed counterparts. Local investors have been suggested to be weary of smart beta because of the lack of a successful track record and questions regarding the transparency of the funds (Cox, 2014). Given this gap in the knowledge about smart beta, especially in the South African context, this study explored possible portfolio optimisation to provide a deeper understanding of smart beta fund performance. While earlier literature on smart beta has focused primarily on fundamental factor selection (see Fama & French, 1998, 2006; Van Heerden, 2014; Hou, Xue & Zhang, 2016), this study aimed to analyse the portfolio construction implications of using various fundamental factors and the classification persistence of stocks.

3.2 RESEARCH DESIGN

In order to address the formulated objectives of this study, meticulous research had to be conducted. Trustworthy recommendations can only be made from data which have been collected and analysed in a scientifically sound way. Therefore, the researcher ensured that sound research methods were in place and that these methods were followed throughout the study to ensure reliable results. In this chapter, the research design of the study will first be discussed, followed by the research methodology that was employed.

It is imperative that an appropriate research design is selected to guide a study. Lee and Lings (2008: 180) describe the research design as a framework that enables a study to effectively examine the chosen research question(s). Thus, the research design framework should describe the research process that will subsequently be followed (Babbie & Mouton, 2001:75). Furthermore, conscientious data collection and analyses are essential to ensure reliable results. The chosen framework to give effect to the research objectives of this study will be outlined next.

3.2.1 Problem definition

It is challenging to identify investment strategies that consistently offer outperformance over the market return in an ever volatile stock market. As a result, investors and asset managers are in search of alpha-generating strategies to at least outperform the diminishing effect of inflation. Here, 'alpha' refers to the excess return above that of the market-related return that is generated by an investment strategy. For instance, if a benchmark portfolio, such as the JSE FTSE All Share Index (ALSI), offers a return of seven per cent and a portfolio offers ten per cent, the portfolio offers roughly a three per cent outperformance, or alpha.

As mentioned earlier, smart beta is a new investment philosophy that combines fundamental factors as described by authors such as Banz (1981), Berk (1995), Fama and French (1998, 2006) and Pástor and Stambaugh (2003), to construct a diversified portfolio. This portfolio, in turn, should generate alpha which is based on the ability of each included fundamental factor to act as a driver of return. The performance and fundamental factor selection of smart beta strategies have been analysed globally (see Titman, Wei & Xie, 2004; Avramov & Chordia, 2006; Van Heerden, 2014; Siu, 2015; Beck *et al.,* 2016). However, limited research has investigated the implications of constructing a portfolio. The process of constructing an optimal smart beta portfolio is still ambiguous. Investors and smart beta fund managers can benefit from understanding the effect of their portfolio management decisions. The portfolio manager's improved understanding in turn, will benefit the investors.

The South African market remains sceptical of smart beta as an effective strategy because there are only a few smart beta funds and their assets under management are small when compared to other institutional funds. Smart beta's ability to generate alpha has been proved in developed markets and prominent asset managers, such as BlackRock, have developed successful smart beta strategies. The popularity of smart beta in developed markets as opposed to emerging markets, such as South Africa, may be attributed to the depth of the market in each respective country. A smart beta multifactor strategy receives signals from each fundamental factor included in the portfolio. In turn, these signals determine whether a specific stock should be held by the portfolio. Changes in signals will indicate that trading of stocks are required, increasing the associated trading costs. Deeper markets typically require lower trading costs than shallower markets, such as the South African market. The question therefore arises how a change in signals should be dealt with to maximise return in emerging markets. This study accordingly investigated the implications of certain smart beta portfolio management decisions.

3.2.2 Research objectives and hypotheses

Secondary research objectives were developed to systematically address and guide the primary research objective. The primary research objective was two-fold: first, to investigate the practical portfolio rebalancing implications of having to buy and sell certain stocks periodically and second, to investigate smart beta stock-classification patterns. The effects of rebalancing on the portfolio include the resultant portfolio churn and after-cost performance over the 2007 to 2016 period.

The secondary objectives and their corresponding hypotheses are as follows:

I. to measure the effect of rebalancing according to various calendar intervals on the net returns of simulated portfolios (Hypothesis 1);
II. to compare each simulated smart beta portfolio's after-cost performance to relevant SWIX and ALSI benchmarks (Hypothesis 2);
III. to identify the main fundamental factor(s) driving returns across the two multifactor portfolio strategies (Hypothesis 3);
IV. to analyse the relationship of portfolio turnover (called churn) with portfolio return and stock classification persistence (Hypothesis 4 and Proposition 1);
V. to measure the probability that a stock that was included in a winner (loser) portfolio for N consecutive months, will remain in the winner (loser) portfolio for N+1 months (N = four-, five-, and six months) (Hypothesis 5);
VI. to compare the classification persistence stability of the best-rated stocks to that of the worst-rated stocks (Hypothesis 6); and
VII. to determine the probability of classification persistence within specific market sectors (Hypothesis 7).

According to Coldwell and Herbst (2004:86), a hypothesis states the existing relationship between two or more variables. The hypothesis is then subjected to tests in order to conclude whether it proposes a viable relationship. Appropriately, this study assessed several hypotheses to address their corresponding research objectives.

These research objectives are discussed in two separate chapters, Chapter 4 and 5. The first chapter containing the results, Chapter 4, will consider the portfolio construction implications which arose from portfolio rebalancing decisions, as measured by its impact on portfolio performance. Research Objectives I, II and III will be discussed in the following section, while their corresponding Hypotheses 1, 2 and 3 will also be subjected to scrutiny in this section.

First, the effect of various rebalancing frequencies on performance can be determined by testing the hypothesis that a more frequent rebalancing strategy will increase the need for trading and subsequently diminish net returns. In other words, increased portfolio rebalancing frequency can reasonably be expected to increase the resultant costs due to the increased trading. It is therefore expected that the net returns for more frequent rebalancing strategies would underperform less frequent rebalancing frequency strategies across all eight possible simulated smart beta portfolios. Four different calendar rebalancing frequencies, namely monthly, quarterly, semi-annually and annually, were compared for each of the eight different portfolio construction methodologies. Assuming that $\mathcal{R}_n$ represents the annualised net returns for every N month(s) calendar rebalancing strategy, Hypothesis 1, which addresses research Objective I, is as follows:

$$H_{1:0}: \mathcal{R}_1 = \mathcal{R}_3 = \mathcal{R}_6 = \mathcal{R}_{12}$$

$$H_{1:A}: \mathcal{R}_1 \neq \mathcal{R}_3 \neq \mathcal{R}_6 \neq \mathcal{R}_{12}$$

Second, the ability of each respective portfolio strategy to generate outperformance was tested. Thus, the ability of the portfolio to outperform the two selected benchmark(s) over the ten-year period in question was examined, assuming that μ_P refers to the mean annualised return of the portfolio and that μ_M refers to the mean annualised return of the benchmark. Therefore, Hypothesis 2, which addresses research Objective II, is as follows:

$$H_{2:0}: \mu_P = \mu_M$$

$$H_{2:A}: \mu_P > \mu_M$$

It was proposed that fundamental factors would not offer the same value within a multifactor portfolio. The specific fundamental factors which drive returns were therefore determined for both multifactor portfolios. Thus, Hypothesis 3, which addresses research Objective III, is as follows:

$H_{3:0}: \beta_x = \beta_y$

$H_{3:A}: \beta_x \neq \beta_y$

The second chapter that will offer the results, Chapter 5, will address the portfolio churn implications due to various portfolio rebalancing frequencies as well as the effects of weak and strong classification persistence of stocks. The remaining research objectives, namely Objectives IV, V, VI and VII will be explained next. Similarly, Hypotheses 4, 5, 6 and 7, as well as Proposition 1, will also be subjected to scrutiny in this chapter.

In order to determine the influence of the rebalancing frequency on portfolio churn, μ_n represents the mean churn of a portfolio which were rebalanced every N months. It can be expected that a more frequent rebalancing frequency would translate to increased portfolio churn. The possible rebalancing frequencies remained monthly, quarterly, semi-annual and annually. Thus, Hypothesis 4, which partially addresses research Objective IV, is as follows:

$H_{4:0}: \mu_1 = \mu_3 = \mu_6 = \mu_{12}$

$H_{4:A}: \mu_1 \neq \mu_3 \neq \mu_6 \neq \mu_{12}$

The last three secondary research objectives, namely V, VI and VII address the classification persistence of stocks. First, it is hypothesised that the classification persistence of a stock is influenced by the time (N) it has already, consecutively been classified within a specific winner (buy), hold or loser (sell) signal for N months. By disproving this hypothesis, it can be concluded that a stock's probability of remaining within its last signal classification is influenced by the amount of time it has already been classified as such. Therefore, it can be expected that current stability indicates future stability. In this case, 'stability' refers to signals remaining consistent and therefore not indicating a need to trade and thereby incurring costs. If φ represents the aggregate classification persistence of stocks (in other words, their probability to not change to a different buy, hold or sell category than the stock has been classified as in for the last n consecutive months). Consequently Hypothesis 5, which addresses research Objective V, is as follows:

$H_{5:0}: \varphi_4 = \varphi_5 = \varphi_6$

$H_{5:A}: \varphi_4 \neq \varphi_5 \neq \varphi_6$

Second, the stability of winner (long) portfolios compared to loser (short) portfolios was measured, indicating whether the classification persistence differed between a positive and a negative signal. It was expected that winner portfolios, and therefore positive buy signals, would be more stable than sell signals. Therefore, Hypothesis 6, which addresses research Objective VI, is as follows:

$H_{6:0:}\, \varphi_L = \varphi_S$

$H_{6:A}: \varphi_L > \varphi_S$

Similar to Hypotheses 5 and 6, the classification persistence of sectors were scrutinised in Hypothesis 7. It was therefore investigated whether certain sectors were more stable than others by comparing the classification persistence of sectors. It is hypothesised that some sectors are inherently more stable than others. Hypothesis 7, which addresses research Objective VII, is therefore as follows:

$H_{7:0}: \varphi_{s1} = \varphi_{s2} = \varphi_{sn}$

$H_{7:A}: \varphi_{s1} \neq \varphi_{s2} \neq \varphi_{sn}$

Finally, research Objective IV was further investigated by considering the relationship between classification persistence and portfolio churn. Proposition 1 states that as classification persistence weakens, in other words the probability of a signal remaining the same for the following period as it was for the preceding consecutive N months, it is expected that portfolio churn will increase due to the signals becoming less stable.

Thus, an inverse relationship was expected between these two variables, namely classification persistence and portfolio churn.

The aforementioned hypotheses and proposition all play a role in making it possible for the researcher to draw conclusions and to provide holistic recommendations. As mentioned earlier, a meticulous data collection and analysis process was followed to cast a credible judgement based on the outcome of the proposed hypotheses. The contributions made by this study and research methodology followed by this study to reach a conclusion is discussed in the subsequent section.

3.3 Proposed contributions to existing literature

Investment professionals, especially fund managers, are in ever-changing competition to outperform the market in order to attract investors. It is essential that different investment strategies are explored in an environment where information is almost instantaneously available. Smart beta strategies are a result of this phenomenon. Smart beta offers investment professionals a strategy to use new information in order to make profitable investment decisions. However, many questions about these strategies still need to be answered.

Previous research has specifically focused on establishing the success of such funds in non-US economies, refining data to account for all the possible statistical biases and determining the optimal order of importance for existing factors. Therefore, this study aimed to build on this existing knowledge by rather focusing on the characteristics and performance of smart beta funds in the South African equity market.

To the knowledge of the researcher, no previous research has been published on the classification persistence of smart beta stocks in the South African equity context. The study's scope was even further expanded by determining which market sectors are more likely to remain within the chosen portfolio. Therefore, sector-specific knowledge will be increased beyond research that was already conducted in the South African context.

Investment professionals, specifically those dealing in smart beta portfolios, may profit from knowing how often to rebalance. This study therefore aimed to offer insight into the implications of using various rebalancing strategies. Consequently, the study considered the trade-off that exists between keeping the smart beta portfolio cost low by not incurring unnecessary trading costs and at the same time maintaining an accurate stock pick according to the selected fundamental factors.

3.4 Research paradigm

One of two key research paradigms is typically used to give effect to academic research, namely a positivistic research paradigm or a phenomenological research paradigm. A positivistic research paradigm hinges on the belief that only by means of factual knowledge that is acquired through observation, including measurement, can reliable information be collected (Crowther & Lancaster, 2008). As a result, the data for a positivistic study are quantifiable and measurable as was the case in this particular study. A positivistic approach subscribes to the conviction that events occur in an observable, decisive and regular manner which enables the researcher to infer certain expectations based on observed events (Crowther & Lancaster, 2008). The study attempted to do just that by comparing the expected signals based on past classification persistence to realised signals. Positivistic research paradigms accordingly make use of a deductive approach, focusing on the facts of the research, while phenomenological studies make use of an inductive approach (Crowther & Lancaster, 2008). A phenomenological research paradigm studies the stories and experiences associated with certain events, instead of studying the scientific facts behind such an event, to draw conclusions (Easterby-Smith, Thorpe, & Jackson, 2012). Given that the study at hand focused on the quantifiable results of measurable observations within the simulated smart beta fund, it was deemed appropriate to follow a positivistic approach.

3.4.1 Quantitative analysis

As the study measured classification persistence within a smart beta portfolio and the level of information it contains, it was deemed appropriate to use quantitative, secondary data. Quantitative data are used to analyse the facts of a reality that is fixed and measurable (Cooper & Schindler, 2014: 161). Qualitative data, on the other hand, assumes a reality that is fluid and negotiable (Cooper & Schindler, 2014: 161). Therefore, using a qualitative approach for this study would be inappropriate, considering that the study measured determinable, numerical movements and relationships within a dataset instead of measuring individuals' perceptions.

The study implemented a panel study of longitudinal nature, as defined by Lee and Lings (2008:198). A longitudinal panel study was deemed appropriate as data were collected and measured at various points in time for the specific sample. As Ang (2015:108) notes, the results of such a study can be used to infer the causality, relationships and time lags on portfolio movements, and more specifically, the information held by classification persistence and its influence on the resulting investment portfolio.

3.4.2 Secondary data collection

To address the formulated research objectives, specific data were needed. As previously highlighted, secondary data were collected for the purposes of this study. The data sample used for this study is the top 100 listed JSE stocks, based on market capitalisation, for the period January 2007 to December 2016. The data analysis process will be discussed in the following sections.

3.4.2.1 Fundamental factor selection

In order to address the research questions, it was necessary to construct a simulated smart beta investment portfolio. First, an appropriate measure of each individual fundamental factor was needed. The selection of the fundamental factors included in the portfolio, was based on the following criteria: support for the factors in prior literature, perceived robustness, their ability to add value to the process of answering the research question and data availability. Subsequently, six fundamental factors were included in the portfolio, namely high yield, investment, profitability, momentum, value and liquidity. These factors were deemed to have sufficient support in prior literature and proved to have adequate data available for the research period in question.

The fundamental factors discussed in the literature review in Chapter 2 are those decided to have sufficient support in prior literature as well as perceived robustness in a global context. Of these fundamental factors that were discussed, two were not included in the final simulated smart beta investment portfolio. The size fundamental factor was excluded as it was perceived to be rather stagnant. As measured by market capitalisation, the signals for the size fundamental factor are unlikely to show large movements. Thus, this fundamental factor was excluded based on the belief that it would not contribute to the process of addressing the formulated research objectives, specifically the effect of weak classification persistence. Also, because of a trading constraint on illiquid stocks, the sample was limited to the top 100 listed stocks on the JSE, based on market capitalisation. Therefore, stocks in this sample would not truly be able to replicate the perceived beneficial part of the size fundamental factor which is derived from investing in smaller, rather than larger stocks. The second fundamental factor that was excluded from the portfolio was volatility. This exclusion was based on the findings of Van Heerden and Van Rensburg (2015) that liquidity does not contribute to excess stock returns in the South African context. These authors conclude that illiquidity is not a robust explanation of excess returns or a priced factor on the JSE (Van Heerden & Van Rensburg, 2015).

The plethora of available fundamental factors in prior literature presents a challenge to a fund manager at the outset of constructing a smart beta fund. However, it must be noted that the primary aim of this study was not to evaluate fundamental factor performance, but instead to examine the interrelationships that exist in a multifactor strategy. Other studies have extensively investigated the value that different fundamental factors contribute. This fundamental factor analysis is not the primary purpose of this study. Instead, the study considered the already constructed portfolio to identify optimal portfolio management strategies. Therefore, the argument to include the six selected fundamental factors for the purpose of studying classification persistence was deemed justified.

3.4.2.2 Measurement metrics per fundamental factor

In order to determine whether a specific stock has a winner (buy) or loser (sell) signal for a specific fundamental factor, the stock must adhere to that factor's requirement. Each fundamental factor has a unique measure as identified in the literature and demonstrated in Table 3.1.

Table 3.1 Selected fundamental factors and their measures

Fundamental factor	**Measure**	**Reference**
High yield (HY)	Rolling twelve-month dividend yield	Graham and Dodd (1951)
Value (VAL)	Earnings yield	Fama and French (2014)
Profitability (PROF)	Return-on-equity (ROE)	Amenc, *et. al* (2015
Investment (INV)	Twelve-month rolling change in total assets	Fama and French (2014)
Momentum (MOM)	Four-month rolling total return	Van Heerden (2014)
Liquidity (LIQ)	Average daily volume traded over one month	Pástor and Stambaugh (2003)

a) High yield

The high yield fundamental factor was measured by the rolling twelve months dividend yield calculated as the sum of all gross dividend-per-share amounts that have become ex-dividend in the preceding twelve months divided by the current stock price. A higher dividend yield is considered to outperform a lower dividend yield.

b) Value

The value factor was measured by the earnings-to-price (earnings yield) ratio. This ratio is a calculation of the projected earnings-per-share divided by the current stock price and indicates the rate at which an investor is expected to capitalise the firm's expected earnings in the coming period. Similar to the high yield fundamental factor, the value fundamental factor also considers a higher indicator (larger earnings-per-share) to be preferred. Thus, higher earnings yield ratios will generate winner signals. While lower earnings yield ratios are expected to generate loser signals.

c) Profitability

According to Amenc *et al.* (2015), the profitability factor is represented by the ROE ratio. Return-on-equity acts as a measure of profitability by indicating how much profit a firm is generating with the capital invested by investors. It is calculated by dividing the net income available to common shareholders by the average common total equity times one-hundred in order to return the ratio as a percentage. Once again, a higher indicator is preferred and will generate positive (winner) signals.

d) Investment

The investment factor was measured by the change in total assets (Fama &French, 2014). Here the total of all long-term and short-term assets as reported on the balance sheet is taken into account. In this study, the change in total assets, as a measure of investment, determined by dividing the current total assets' value, by the minimum total assets value in a look-back period. The maximum change in total assets over the specific period is therefore the investment factor measurement.

As investment projects do not immediately deliver returns when capital is invested, it was deemed necessary to incorporate a look-back period for this fundamental factor. Also, without the incorporation of a look-back period, data would show sporadic large changes and longer periods of no change. Therefore, accurate signals that consider all information would be difficult to generate. Three different possible look-back periods were then considered, namely six months, twelve months and twenty-four months. In order to evaluate which period would generate the best returns for the fundamental factor, the latter's performance across varying rebalancing frequencies were evaluated. The six-month look-back period proved to be too short to overcome the last-mentioned problem and therefore, long periods of no signals were still generated under this look-back strategy. The twelve and twenty-four month look-back periods generated very similar returns across various rebalancing frequencies. These two look-back strategies proved to have no statistically significant difference (see Annexure D). In order to select a strategy, the maximum drawdowns and upsides were compared. In both cases the twelve-month look-back period proved to outperform as it had the maximum upside and the minimum drawdown. As a result, the twelve-month look-back strategy was selected.

The investment fundamental factor shows preference towards low investment strategies. A small positive change in total assets is preferred. This positive signal is not shared by negative changes in total assets or no change in total assets. Thus, when ranking the change in total assets to select the top and bottom thirty stocks, null changes and negative changes in total assets were excluded and resultantly assigned a neutral ranking.

e) Momentum

Similar to Van Heerden (2014), momentum was measured by means of measuring the change in total return. The study at hand used a four-month rolling total return to measure the momentum fundamental factor. Total return takes into account all financial gains or losses that would have influenced an investor, such as price movements and dividends. A positive price momentum is assumed to outperform and will generate positive signals as a result.

f) Liquidity

Finally, the liquidity factor was measured by studying the average monthly volume traded (Pástor & Stambaugh, 2003). The daily volume traded data were collected, but as all other fundamental factors were represented monthly, the daily volume traded was processed to represent the average volume traded for that specific month. Therefore, 'volume traded' here refers to the actual number of stocks that were traded of that specific stock.

Finally, a few additional data points were required to be able to test all the hypotheses. More specifically, the monthly total return of each stock was used to calculate the portfolio performance as it takes into account all income-generating factors, such as dividends. Total return was therefore deemed a more appropriate measure of portfolio performance than the closing price. The benchmark total return was needed to determine portfolio performance. Therefore, the Shareholder Weighted All Share Index (SWIX, code: J403t) and the All Share Index (ALSI, code: J203t) monthly total return data were collected from IRESS (IRESS Expert, 2017).

3.4.2.3 The period under analysis

In order to maximise the scope of the results, it was advisable to study a longer period of time. Therefore, the initial period suggested for this study was a fifteen-year period, namely January 2002 to December 2016. However, at the outset of the data collection process, it was evident that the available data were insufficient for the first five-year period of 2002 to 2006. Therefore, the initial period was amended to cover a ten-year period, namely January 2007 to December 2016.

This ten-year period still made it possible for the study to analyse the data that were collected from a pre-, during, and post-financial crisis period. Thus, should it be concluded that the information contained in classification persistence strength maintained its value throughout varying economic stability, the conclusions based on the results can be extrapolated to have value throughout the economic cycle.

3.4.2.4 Data collection sources

In order to ensure that reliable data were collected, the principles as described by Cooper and Schindler (2014: 104-105) were used when data sources were assessed. As this study used existing data bases, or secondary data, the data were collected from credible and reliable sources instead of collecting data by means of interacting with respondents through questionnaires and interviews. The majority of data for this study were collected from Bloomberg (2017), a leading software, data and media company.

Cooper and Schindler (2014: 104-105) list a number of factors which should be taken into account to evaluate the credibility of a data source. Bloomberg is considered a trustworthy source of data as it satisfies all these requirements. First the original purpose of data collection by the source was considered. The documentation of financial data forms part of Bloomberg’s core business activities as a software, data and media company. Second, the source’s credentials were considered. Bloomberg is a recognised source of financial data, in both the academic and industry circles and have been used for a myriad of academic research papers. Third, the data’s date of publication was considered in the case that it can become outdated. However, owing to the nature of the data, it can not be considered outdated. The aim was to evaluate movements in the data over a period of time and therefore the historical availability was deemed necessary. Finally, the data are evaluated as to whether it could be considered open for interpretation. The nature of the data was such that it was numerically factual and recorded as fact. Additionally, the specific data required were typically financial data which were recorded from audited financial statements or market movements that truly occurred. Therefore, it can be concluded that the data were not open for interpretation. This study was conducted with the trust that the data collected from Bloomberg can be considered credible.

Certain additional data from sources other than Bloomberg were needed to complete the study, namely earnings yield and trading costs. It was found that the Bloomberg database pertaining to earnings yield was lacking. These were collected from the IRESS database, which is also considered to satisfy the requirements of a credible data source, as listed by Cooper and Schindler (2014:104-105). Finally, applicable trading costs were gauged by consulting with asset management industry participants from PSG Wealth and Prescient Investment Management.

The research collection methodology, as described in the preceding sections, enabled the study to continue in its aim to give effect to the research objectives. These research objectives were realised by processing and analysing the data as will be discussed in the following section.

3.5 DATA ANALYSIS

In order to address the relevant research objectives, it was necessary to analyse the resultant simulated smart beta portfolios statistically. A portfolio model was constructed using the collected data as described in the previous section. This model aimed to replicate smart beta funds which could exist in the South African market context. Therefore, existing smart beta funds such as the Fairtree Smart Beta Prescient Fund, the Salient Risk Optimised Momentum Fund and the Salient Value Index Fund, were investigated to understand the smart beta funds that were functioning successfully in the South African environment at the time of the study. The resultant simulated portfolios that were constructed for the purposes of this study are explained next.

3.5.1 Modelling the simulated smart beta portfolio

The construction of the simulated portfolio was primarily guided by knowledge of prior smart beta studies as discussed in Chapter 2 (see Fama & French, 2006; Van Heerden, 2014; Hou, Xue & Zhang, 2014). More specifically, the underlying fundamental factor drivers of return were implemented to construct single-factor portfolios as well as two multifactor portfolios. The process of preparing and shaping the data that were collected for the sample of top 100 JSE listed stocks into a working simulated smart beta portfolio is discussed next.

3.5.1.1 Data preparation and assumptions

The aim of preparing the data was to ensure the validity of the results. By studying the original data that were collected, a few short-term gaps in information were identified. For instance, the total assets reported for a specific stock was reported for a period of time in which a month's data point was missing. A linear model was used to fill these gaps. Therefore, the model assumed that a short-term change can be expected to occur in a steady, proportionate manner. This method was implemented in the belief that it would increase the validity of the results. A missing data point would fail to generate any signal to determine whether a stock should be included in a portfolio. Therefore, should a portfolio have positive signals for a period, and then have a missing data point, it would be replaced by another stock with a positive signal in the portfolio. Therefore, churn occurs due to false signals generated by missing data points, rather than actual positive changes in the data. To ensure that the results are conservative, but correct rather than based on false signals, the data were filled for short-term missing data points. 'Short term' here refers to periods of no longer than six months. Thus, if two years of data were missing, that stock was excluded from the portfolio investment options for that period. The use of this linear model process is further justified by the fact that the primary objective of the study was to examine classification persistence. False signals would necessarily lead to weaker classification persistence than the true data could reasonably be expected to have as a result. Thus, the use of a linear model to fill data points is justified from the perspective of rather being conservative to avoid false signals and their effects on the final results of the study.

3.5.1.2 Portfolio construction

In order to sufficiently test all the hypotheses, several portfolios were constructed:

i. Six single-factor portfolios were constructed using the selected fundamental factors.
ii. Two multifactor portfolios were also constructed as a measure of interaction between fundamental factors:
    a. The fundamental factor performance history weighted (FFPHW) portfolio weights the fundamental factor signals relative to each individual fundamental factor's recent performance. This strategy is a new contribution to the existing body of knowledge on smart beta.

b. The equal-weighted multifactor (EWMF) portfolio equally weights each fundamental factor signal.

All eight strategies were followed as long-only (winner) portfolios and short (loser) portfolios. Thus, the winner portfolios simply ignored the loser signals and only traded on the positive signals. These portfolios were constructed as follows:

The inclusion or exclusion of stocks in the investment universe consisting of the top 100 JSE listed stocks at the time was based on signals displayed by the fundamental factor measures. The investment universe was selected as the size of the stocks afforded liquidity and therefore investability to the portfolios. To identify these signals, portfolios were separated by three possible signals, namely a winner (buy), a neutral, or a loser (sell) signal. Similar to Hou, Xue and Zhang (2014), all data at a specific point in time were ranked and the best thirty stocks were considered a winner signal, while the worst thirty were considered a loser signal. The stocks in the middle returned a neutral signal for that period. Whether a stock fell within the best or worst-ranking was based on prior literature defining whether a higher or a lower ratio was desired. Stocks were awarded a high or low designation based on their ranking in the sample at that time. Thereafter, they were identified as a winner, neutral or loser signal and traded within the portfolio as such.

For instance, the high yield fundamental factor is based on the phenomenon that high dividend yield stocks tend to outperform low dividend yield stocks (Graham & Dodd, 1951). Thus, the high yield fundamental factor portfolio identified the thirty stocks with the highest dividend yield as a high ranking and those with the smallest dividend yield as a low ranking. The high- and low-ranking stocks were then assigned a winner or loser signal, respectively. In comparison, the value fundamental factor as measured by earnings yield assigned a winner signal to the low-ranking stocks and a loser signal to the high-ranking stocks.

Corresponding single-factor portfolios were then constructed based on these signals by following an equal-weighting strategy. Given that smart beta strategies were developed to combat the generally used market capitalisation weighted strategies, it seemed appropriate to use an equal-weighting strategy instead. By bypassing the market capitalisation weighting strategy, overweighting overpriced stocks purely due to the chosen weighting strategy was avoided. Instead, each stock falling in the thirty winner signal stocks was assigned an equal weighting of 3.33 per cent, that is a 100 per cent divided by thirty stocks.

The multifactor strategies in turn applied the winner and loser signals of the single-factor strategies in order to construct a combined portfolio. Both portfolios considered all six selected fundamental factors when selecting stocks to trade. The EWMF portfolio equally weighted the top thirty stocks as a long position. In the case of a short portfolio strategy, the bottom thirty stocks would represent the loser position. In order to determine which stocks could be classified as the top and the bottom thirty, the following ranking strategy was employed: First, a cumulative score for each stock per period was determined. Should a stock be classified as a winner signal by three different fundamental factors, a neutral signal by one fundamental factor and a loser signal by the remaining two fundamental factors, it would have a cumulative score of one. Since there were six fundamental factors and a stock could either have a winner (+1), a neutral (0) or a loser (-1) signal for each, the possible scores ranged from a negative six (-6) to a positive six (+6). The best- and worst-performing thirty stocks per period were then selected based on their respective cumulative scores.

Another level of ranking was needed to select the final stocks to be included in the top or bottom thirty. Should twenty-eight stocks have a definitively superior ranking, they were all included in the selected thirty stocks. To select the remaining two stocks to join the already selected twenty-eight stocks in the winner signal classification, price momentum was used. All the stocks with the cumulative score just after the last included score were ranked based on their price momentum performance. Price momentum here incorporated a look-back period of a year as it examined the rolling twelve-month price momentum to establish a ranking. Based on this ranking, the stocks on the verge to be classified as either a winner or a neutral signal, based on their cumulative score, could be classified based on their price-momentum ranking. The two best-performing stocks in the tested cumulative score category were classified as winners and the remaining stocks were classified as neutral. As a result, each period had thirty stocks with a winner classification and thirty with a loser classification. The EWMF portfolio therefore gave an equal weight to each signal from all six fundamental factors.

In contrast to the EWMF portfolio, the FFPHW portfolio gave a higher weighting to the signals of the better performing fundamental factors. Based on a rolling twelve-month total return measure, each single-factor portfolio performance was ranked to determine its relative performance to the other factors. Accordingly, the best-performing single-factor portfolio was assigned a higher weight than its worst-performing counterparts. More specifically, the best-performing fundamental factor carried a weight of forty per cent, then twenty-five per cent, fifteen per cent, ten per cent and the two worst-performing single-factor portfolios were each assigned a five per cent weight. Each single-factor portfolio's signals were then incorporated to have a weighted score per fundamental factor. The sum of the weighted scores was then used to construct the FFPHW portfolio. The formula to compute the final weighted cumulative score for the FFPHW portfolio is as follows:

$$WS_t = \Sigma\,(s_{sfp_t} \times w_{sfp_t}) \qquad \text{(Eq. 3.1)}$$

Where:

$\mathrm{WS_t} =$ a stock's final weighted signal at time t

$\mathrm{s_{sfp_t}}$ = original signal of the single-factor portfolio for that specific stock at time t

$\mathrm{w_{sfp_t}}$ = weight of a specific single-factor portfolio based on ranking for time t

Based on the final weighted cumulative score per stock per period, the final FFPHW portfolio signals could be calculated. Similar to the single-factor and EWMF portfolios, the top thirty ranked stocks were classified as winners and the bottom thirty stocks were classified as losers. An equal-weighted strategy was implemented to build the resulting FFPHW portfolio based on the generated signals. Thus, as opposed to the EWMF portfolio strategy, each signal from all six fundamental factors was not assigned equal importance. Thus, identifying good-performing fundamental factors to include in a portfolio became less critical in this portfolio strategy as outperforming fundamental factors were overweighted and underperforming fundamental factors were underweighted.

As with the EWMF portfolio, stocks with overlapping signals were again ranked based on their twelve-month rolling price momentum. The best-performing stocks were chosen to ensure that exactly thirty stocks were classified as a winner signal and thirty as a loser signal.

Thus, six single-factor and two multifactor portfolios were constructed. These eight portfolios were used to address the research objectives by testing their relevant hypotheses. To address the primary research objective, the classification persistence of each portfolio was determined. Finally, in order to test the remaining hypotheses, namely Hypotheses 4, 5, 6 and 7, the resultant portfolio effects, churn and performance in particular, were also determined.

3.5.1.3 Classification persistence

Classification persistence refers to the stability in signals generated by each stock's individual rating per fundamental factor. In other words, if a stock was classified as a winner for N consecutive months, what would the probability be of that stock's signal remaining a winner for the following month? A weak classification persistence indicates that stocks are constantly changing signals and identifies a possible need to trade.

The classification persistence was tested based on the winner, neutral and loser signals generated. Appropriately, each signal had a numerical representation. A winner classification was represented by number one (1), a neutral classification as two (2) and a loser classification as three (3). The numerical representation of these signals simplified the statistical analyses which followed to determine the probabilities of signals remaining unchanged. The statistical analyses are discussed in further detail in the following sections.

3.5.1.4 Portfolio churn and performance

Supporting the research objectives focusing on classification persistence, the resultant effects on the portfolio were determined. As proposed by the hypotheses, it was expected that weak classification persistence would increase churn and thus trading costs, which in turn would decrease the net returns. Monthly, quarterly, semi-annual and annual calendar rebalancing strategies were tested in order to determine the resultant portfolio churn and performance.

In order to measure the total churn per rebalancing period, the weight per stock at the end of each rebalancing period was calculated. Thus, the sum of the absolute changes needed to rebalance back to the 3.33 per cent initially assigned to each stock is equal to the churn per period. The following formula was used to determine the churn per period:

$$weight\ per\ stock_i = w_{i,t+1} = \frac{w_{i,t-1}(1+r_{i,t})}{\sum_{j=1}^{30}(w_{j,t-1}(1+r_{j,t}))} \qquad \text{(Eq. 3.3)}$$

$$portfolio\ churn\ per\ period = \sum_{n=1}^{30} |\ w_{j,t+1} - w_{j,t-1}\ | \qquad \text{(Eq. 3.4)}$$

Where:

r_t = return of stock for period before rebalancing

$w_{i,t-1}$ = equal weight originally assigned to each stock

$w_{i,t+1}$ = weight of stock i right before rebalancing occurs

Several performance calculations were used. The following performance calculations were conducted:

i. Cumulative ten-year performance (total research period);
ii. Annualised after-cost performance; and
iii. Annualised market adjusted after-cost performance.

a) Trading costs

In order to determine after-cost performance, estimated trading costs were gauged by consulting industry participants from both Prescient Investment Management and PSG Wealth. The resultant estimated trading costs considered brokerage costs, STRATE settlement costs, investor protection levy, value-added tax (VAT) and securities transaction costs (STT) (buy trades only). Short-selling costs also considered the cost of borrowing. Furthermore, less liquid stocks had a higher estimated cost of borrowing than their more liquid counterparts. This increased cost was due to an increased level of risk for short-selling those stocks. Considering that costs are determined largely due to the value of the trade being executed, a portfolio of institutional size was assumed in excess of R500 million.

The relevant costs which were implemented in this study are summarised as follows, where ‘bps’ refers to basis points:

i. The winner portfolios were subjected to trading costs of 50 bps;
ii. The loser portfolios were subjected to 70 bps (large-cap) and 75 bps (mid-cap) due to the additional expenses incurred when short-selling stocks; and
iii. The distinction between large- and mid-cap stocks was made for short-selling as the lack of liquidity in this market had a material effect on the costs of trading.

b) Benchmarks

Both the SWIX and the ALSI were used as benchmarks comparisons. However, the portfolio mandates focus to outperform the SWIX rather than the ALSI. The SWIX was introduced in 2003 to improve the single stock concentration risk that is present in the ALSI. The SWIX is preferred as it is a free-float adjusted market capitalisation weighted index which determines the market capitalisation of constituent stocks based on that recorded in the South African stock register as maintained by STRATE, excluding foreign shareholdings. The current smart beta funds functioning in South Africa often use the SWIX as a benchmark. Therefore, the SWIX was considered a better benchmark than the ALSI. The market-adjusted performance was, however, determined on both the SWIX and ALSI throughout the study.

c) Investment value of fundamental factors

Finally, the investment value of fundamental factors was evaluated. Fundamental factors were evaluated based on the ability of the winner portfolio to outperform the loser portfolio. If the fundamental factor successfully identifies potential out- and underperforming stocks, the winner portfolio should outperform the loser portfolio. Larger differences between the winner and loser portfolios indicated better investment value for the fundamental factor. Similar to the suggestion by Fama and French (1993), the investment value of the six fundamental factors were determined by measuring the difference between the winner and the loser portfolios. Table 3.2 summarises the tests that were performed to measure the investment value of the fundamental factors.

Table 3.2: Fundamental factor performance evaluation

Fundamental factor	Test	Calculation
Value (VAL)	HML (high minus low)	High earnings yield portfolio minus low earnings yield portfolio
Profitability (PROF)	HML	High return-on-equity (ROE) portfolio minus low ROE portfolio
Momentum (MOM)	HML	High price momentum portfolio minus low price momentum portfolio
Liquidity (LIQ)	IML (illiquid minus liquid)	Illiquid portfolio return minus liquid portfolio return
Investment (INV)	RMW (robust minus weak)	Robust portfolio ((low change in total assets) minus weak portfolio (high change in total assets)
High yield (HY)	HML	High dividend portfolio minus low dividend portfolio

The simulated smart beta portfolios enabled the study to examine the interrelationships that occurred in different smart beta portfolios in practice. Care was taken to construct portfolios closely mimicking possible institutional portfolios. Therefore, it is expected that the results of the study can be replicated in smart beta portfolios in practice in the South African environment, and that the recommendations of the study can be implemented in practice.

3.5.2 Descriptive data analysis

Anderson, Sweeney and Williams (2011: 13) define descriptive statistics as a means of creating summaries of a specific dataset. An outsider can therefore merely study these descriptive statistics as a way to obtain an oversight of the dataset in question. Descriptive statistics include numerical measures such as measures of location, distribution shape and variability.

Heat maps are used to provide a visual perspective of the data. Heat maps use colour coding to effectively portray information about a specific dataset. This study uses shades ranging from green to red. More favourable numbers are portrayed by a green shade, whereas les favourable numbers are indicated by red shades. It is therefore possible for the reader to instantly be able to draw conclusions from the dataset represented in Chapters 4 and 5 because of the visual representation of data.

Investment portfolios typically display fund information in fund fact sheets. Appropriately, a fund fact sheet was compiled for each of the multifactor strategy portfolios, EWMF and FFPHW. These fund fact sheets display information which may be relevant to an investor considering investing in these two funds. Descriptive statistics, such as mean returns and standard deviation as a measure of risk are indicated. The fund fact sheets therefore aim to give an outsider insight into the fund and the underlying supporting data, which is in line with what Anderson *et al.* (2011: 13) describe as the aim of descriptive statistics.

3.5.3 Inferential data analysis

Berenson, Levine and Krehbiel (2005: 3) define inferential statistics as a means to test the characteristics of a population. Inferential statistics allow a study to generalise the results by using statistical inference on the sample data. It can therefore be expected that results maintain their accuracy outside the scope of the sample used for a study. The results obtained in this study can therefore be expected to hold for future time periods and can be helpful to smart beta fund managers.

Inferential statistics are therefore crucial to being able to make reliable and valuable conclusions and recommendations which could extrapolate the results of this study to be used in the industry. The research objectives were divided and discussed in two separate chapters. First, the eight portfolios, namely the six single-factor portfolios and the two multifactor portfolios, were analysed. These analyses addressed research Objectives I, II, III and IV. The aim was to analyse the interconnections that could arise as a result of various portfolio rebalancing strategies using inferential statistics. For instance, the influence on portfolio churn and performance due to selecting various rebalancing frequencies were measured. To give effect to research Objectives I, II, III and IV several *t*-tests were conducted to test the relationship between specific variables. The portfolios were also subjected to correlation tests to measure the degree to which portfolios moved in relation to one another. Finally, a regression analysis was conducted to give effect to research Objective III. Thus, the HML tests as previously explained were used to identify the contribution of each fundamental factor to the resultant multifactor portfolio performance. The drivers of return in the multifactor portfolios could therefore be determined by conducting regression and LASSO analyses on the HML results.

3.5.3.1 Analysis of variance (ANOVA)

An analysis of variance (ANOVA) test is used to analyse the difference in groups of data. Research objectives comparing different variables therefore apply ANOVA tests to determine whether the groups significantly differ from each other. Research Objectives I, II, IV, VI and VII were, at least partially, addressed by means of conducting ANOVA tests. The differences measured were between:

i. after-cost returns under different rebalancing strategies;
ii. after-cost returns and benchmark returns of the SWIX or ALSI;
iii. portfolio churn under different rebalancing strategies;
iv. the classification persistence of the best (winner) and worst (loser) stocks; and
v. the classification persistence of different market sectors.

The result of an ANOVA test is statistically significant, justifying the rejection of the relevant null hypothesis, if the absolute p-value of the test is larger than the absolute critical value. All ANOVA tests throughout this study were conducted at a five per cent significance level.

3.5.3.2 The LASSO model

The least absolute shrinkage and selection operator (LASSO) as introduced by Tibshirani (1996) is a regression analysis technique. The LASSO model performs regularisation and variable selection in an attempt to improve the prediction accuracy of regression models. Essentially, the model shrinks the coefficients of variables included in the original model towards zero. This shrinking process ensures that only the most valuable variables remain included. The LASSO model is a sparse model as it only involves a subset of the variables included in the original model (Tibshirani, 1996). The LASSO model is considered a soft-thresholding model (Hastie, Tibshirani & Friedman, 2013). In contrast to the LASSO model the traditional stepwise models act as hard-thresholding models as they restrict the linear regression model as it aims to identify a subset of p predictors that are believed to be related to the original model response. The LASSO aims to translate each coefficient by a certain value of 'Lamda' (λ), truncating at zero.

Equation 3.3 illustrates how the regression coefficient, $\hat{\beta}_{lasso}$, was obtained:

$$\underset{\beta}{\text{minimise}} \sum_{i=1}^{n}\left(y_i - \beta_0 - \sum_{j=1}^{p}\beta_j x_{ij}\right)^2 + \lambda \sum_{j=1}^{p}\left|\beta_j\right| = RSS + \lambda\sum_{j=1}^{p}\left|\beta_j\right| \qquad \text{(Eq. 3.3)}$$

Otherwise stated, the LASSO coefficients are the solutions to the L_1 optimisation problem:

Minimise $(\boldsymbol{y} - \boldsymbol{Z}\beta)^T(\boldsymbol{y} - \boldsymbol{Z}\beta)$ subject to $\sum_{j=1}^{p}\left|\beta_j\right| \leq s.$ (Eq. 3.4)

Thus, for every value of λ there is a corresponding value of s, which limits how the data are fit to the extent that equations 3.3 and 3.4 are able to determine the LASSO coefficient.

Figure 3.1 Standardised LASSO coefficients for a hypothetical dataset, as a function of log (λ)

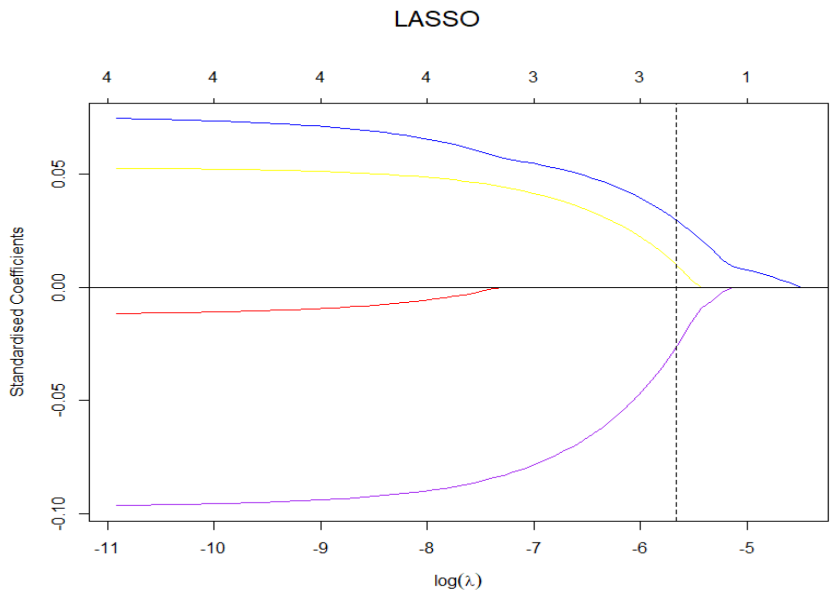


Figure 3.1 illustrates the LASSO coefficient estimates for a hypothetical dataset. λ is essentially null to the left of the plot. As λ increases, the LASSO coefficient estimates shrink towards zero as indicated in equations 3.3 and 3.4. The model performs variable selection as it can identify any optimal number of variables, or largest drivers of return

for the purposes of this study, for a specific value of λ. The LASSO is considered particularly advantageous thanks to its prediction accuracy and therefore its ability to identify core drivers of return. It was therefore deemed appropriate for the purposes of this study to assist in exploring research Objective III. Thus, the LASSO model was used to identify the fundamental factors that drive returns in the multifactor portfolio. The code used to apply the LASSO model was implemented in the RStudio interface (See Annexure E).

The second results chapter, namely Chapter 5, will discuss the results of the primary research objective, namely classification persistence. First, a frequentist approach to probability was used to address research Objective V. Frequentism interprets probability as an event's expected frequency of occurrence over the long term. Here the probability was measured by the relative frequency of the event occurring, observed by multiple repetitions of the experiment (Neyman, 1977). The resultant probabilities therefore depicted the classification persistence of the various smart beta portfolios. Further inferences were then made based on the classification persistence. Multiple *t*-tests, correlation analyses and regression tests were conducted to further explore the classification persistence. Resultantly, the remaining research objectives, namely Objectives 4, 5, 6 and 7 were addressed.

3.6 CONCLUSION

In this study, explanatory research into the interdependency present within smart beta portfolios was conducted. This interdependency can arise due to portfolio management decisions, such as rebalancing frequency and fundamental factor inclusion, or as a result of fundamental factor stability. A positivistic research paradigm was deemed appropriate to examine the secondary quantitative data and consequently give effect to all the research objectives.

Six fundamental factors were selected namely, value, profitability, momentum, liquidity, investment and high yield. Two equally weighted multifactor strategies namely, EWMF and FFPHW, were constructed using different portfolio construction methodologies. These eight simulated smart beta portfolios (six single-factor and two multifactor) enabled the analysis of the interdependency which resulted from portfolio management decisions. Therefore, the portfolios were each subjected to different possible rebalancing frequencies to determine the resultant effects on portfolio performance and churn. The key variables in the statistical analyses included classification persistence, portfolio churn and net returns.

By using the research methodology as described in this chapter, the study aims to infer several portfolio optimisation recommendations for fund managers who implement a smart beta investment philosophy. The following two chapters offer the results obtained from the research methods that were described in this section.

CHAPTER 4

INVESTMENT PORTFOLIO CONSTRUCTION IMPLICATIONS AND DRIVERS OF RETURN

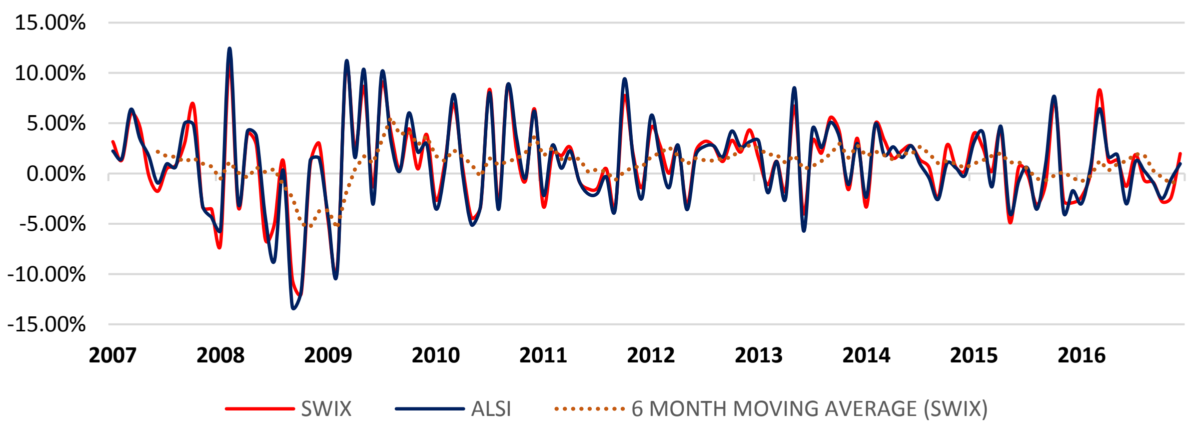
4.1 INTRODUCTION

The investment value derived from the winner versus the loser stocks of each fundamental factor will be explored in this chapter. The portfolio-construction implications due to using six different fundamental factors will be discussed. The implications of applying monthly, quarterly, semi-annual or annual calendar rebalancing on the portfolio's net returns will also be calculated and explained. This chapter therefore addresses Objectives I, II and III. At the conclusion of Chapter 5, the fund fact sheets will summarise the typical information desired by an investor when deciding whether to allocate capital to a specific fund. These fund fact sheets will therefore summarise selected information from Chapters 4 and 5.

4.2 SOUTH AFRICAN EQUITY MARKET CONTEXT

In the midst of the volatile South African economic environment opportunity exists. Smart beta investment strategies aim to identify stocks which will outperform the market due to their inherent qualities. Figure 4.1 displays the volatile environment in which the proposed simulated smart beta portfolios were tested.

Figure 4.1 ALSI and SWIX monthly returns



Source: Adapted from IRESS expert (2017).

Overall, the South African economy realised positive returns over the ten-year research period as can be seen by the six-month SWIX moving average line in Figure 4.1. However, the market does prove to be rather volatile. As a result of the investment risk-return trade-off, there is ample opportunity for return in such a volatile environment. Stated otherwise, the South African environment offers considerable profit opportunities should the correct investment strategy be followed.

Negative returns were realised for two specific time periods between 2007 and 2016. First, the 2008/9 global financial crisis affected financial markets worldwide. The South African economy, as a relatively small, open economy, is reliant on foreign trade and foreign direct investment (FDI). As the global financial crisis worsened, the South African economy and its financial markets displayed the effects of the global economic slowdown as is evident in Figure 4.1.

Existing economic obstacles, such as the high unemployment rates deteriorated during this time of global financial distress. Unemployment rates as high as 25 per cent had a negative impact on economic growth (Statistics South Africa, 2017). However, while facing global financial turmoil and local economic instability, the South African equity market managed to recover by early 2009. This recovery is shown in Figure 4.1. Throughout the period, the South African equity market remained volatile. This volatility may be attributed to various factors including political instability, economic downgrades by global rating agencies and high unemployment rates.

The second negative return period during 2015 and 2016 was as a result of the large concentration risk that was present in the South African equity market. The South African equity market is concentrated, because of a few large stocks, which leads to substantial changes in the indices due to changes in a few, or even only one firm. Thus, the risk increased due to the excessive sensitivity to movements of these few stocks. Naspers Limited (JSE: NPN) is a prime example. At approximately one-fifth of the JSE Top40 Index since 2014 by market capitalisation, changes in the Naspers stock price alone can visibly affect the index performance. The shareholder weighted index (SWIX) attempts to account for this market concentration. However, the SWIX has not completely managed to dilute the influence of these large firms.

The resultant smart beta single- and multifactor portfolio performance and how it managed to out- and underperform in this environment will be discussed in the following section.

4.3 INVESTMENT VALUE DERIVED FROM INDIVIDUAL FUNDAMENTAL FACTORS

Two simulated smart beta multifactor portfolios were constructed using two diverse methodologies as explained in Chapter 3. Six fundamental factors were selected to construct these two portfolios. The aim of this study was not to evaluate the performance of smart beta strategies, but rather to analyse the interdependencies that arose within the portfolio and the information contained therein. The investment value of a fundamental factor here refers to the ability of a fundamental factor to correctly identify the potential out- or underperforming stocks. Therefore, an analysis of fundamental factor performance was needed to determine the investment value held by the fundamental factor for the South African equity markets. Research Objectives I and III are partially addressed in this section as it studies the influence of varying rebalancing frequencies and the drivers of return respectively.

Figure 4.2 indicates the cumulative net returns of each fundamental factor's winner and loser portfolio. The cumulative return if a nominal amount of R100 was invested on 1 January 2007 is displayed. The solid lines in Figure 4.2 represent winner portfolios while the dotted lines represent loser portfolios. The position of each winner portfolio in correlation to its respective loser portfolio indicates the fundamental factor's investment value in the South African context. A fundamental with a high investment value will correctly identify out- and underperforming stocks for winner and loser portfolios. Thus, the winner portfolio should outperform the loser portfolio over both longer and shorter periods. A bigger difference between these two portfolios indicates a higher investment value held by that specific factor. No investment value is derived where the winner and loser portfolio generate very similar returns.

As illustrated in Figure 4.2, the difference between the winner and loser portfolios decreases as rebalancing frequency decreases. The investment value derived from the fundamental factors therefore diminishes as the rebalancing frequency decreases.

Figure 4.2 Cumulative net return per fundamental factor (2007– 2016)

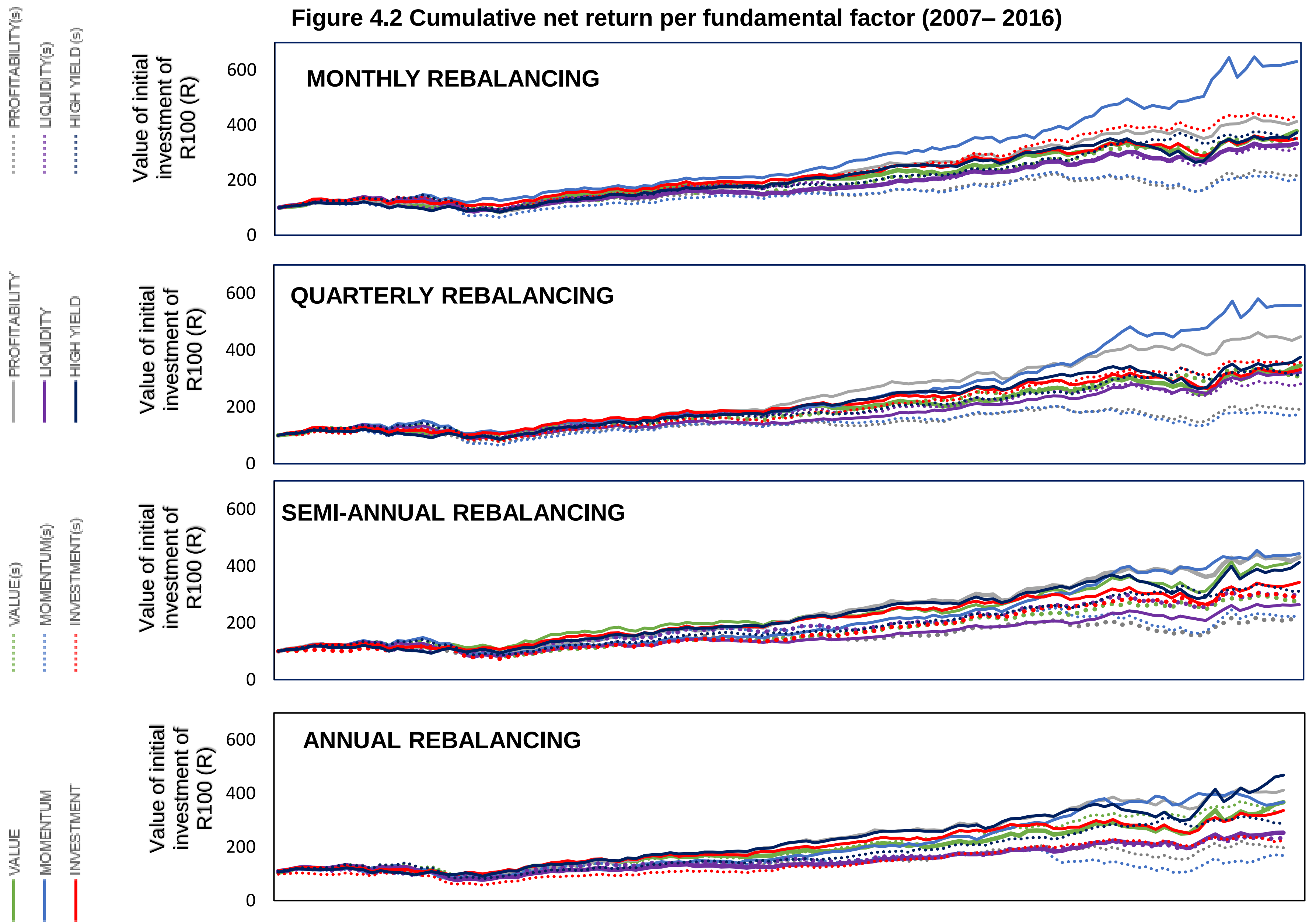


Figure 4.3 indicates the cumulative net returns as reflected in Figure 4.2 within three distinct periods, namely crisis, post-crisis and market recovery periods. The solid lines represent winner portfolios while the dotted lines represent loser portfolios in Figure 4.3. The aim here is to clearly identify whether the investment value derived from fundamental factors has changed significantly during the ten-year period under analysis. The hypothetical initial R100 investment is therefore reset every three years and three months.

It is evident from Figure 4.3 that the investment value derived from the fundamental factors differs over time. Several fundamental factors have different levels of investment value during periods of post-financial crises than it displayed during the 2008/9 financial crisis. The last period specifically indicates more investment value than the first two periods.

Finally, Figure 4.4 displays the winner minus the loser portfolio movements for the ten-year period. Prior literature has evaluated fundamental factor strength by studying the outperformance of the winner portfolio as compared to the relevant loser portfolio. Thus, a positive (negative) return indicates out- or underperformance. Again, the cumulative return if investing R100 initially is determined.

The fundamental factor strength does not move in correlation to one another as can be seen in Figure 4.4. This is specifically observed in the two periods of negative growth that has already been identified in Figure 4.1. Several fundamental factors, such as momentum and profitability, therefore reacted positively to the financial crisis and concentration risk observed in the beginning and at the end of the research period respectively. This reaction suggests a diversification benefit to invest in these fundamental factors during periods of inverse correlation as some fundamentals reacted differently to certain risks than the general market.

The individual fundamental factors are the constituents of the multifactor portfolios discussed later in this chapter. It is therefore essential to understand the individual factor investment value. The characteristics of the individual fundamental factors will be discussed in detail in the following section.

Figure 4.3 Re-adjusted fundamental factor cumulative net return

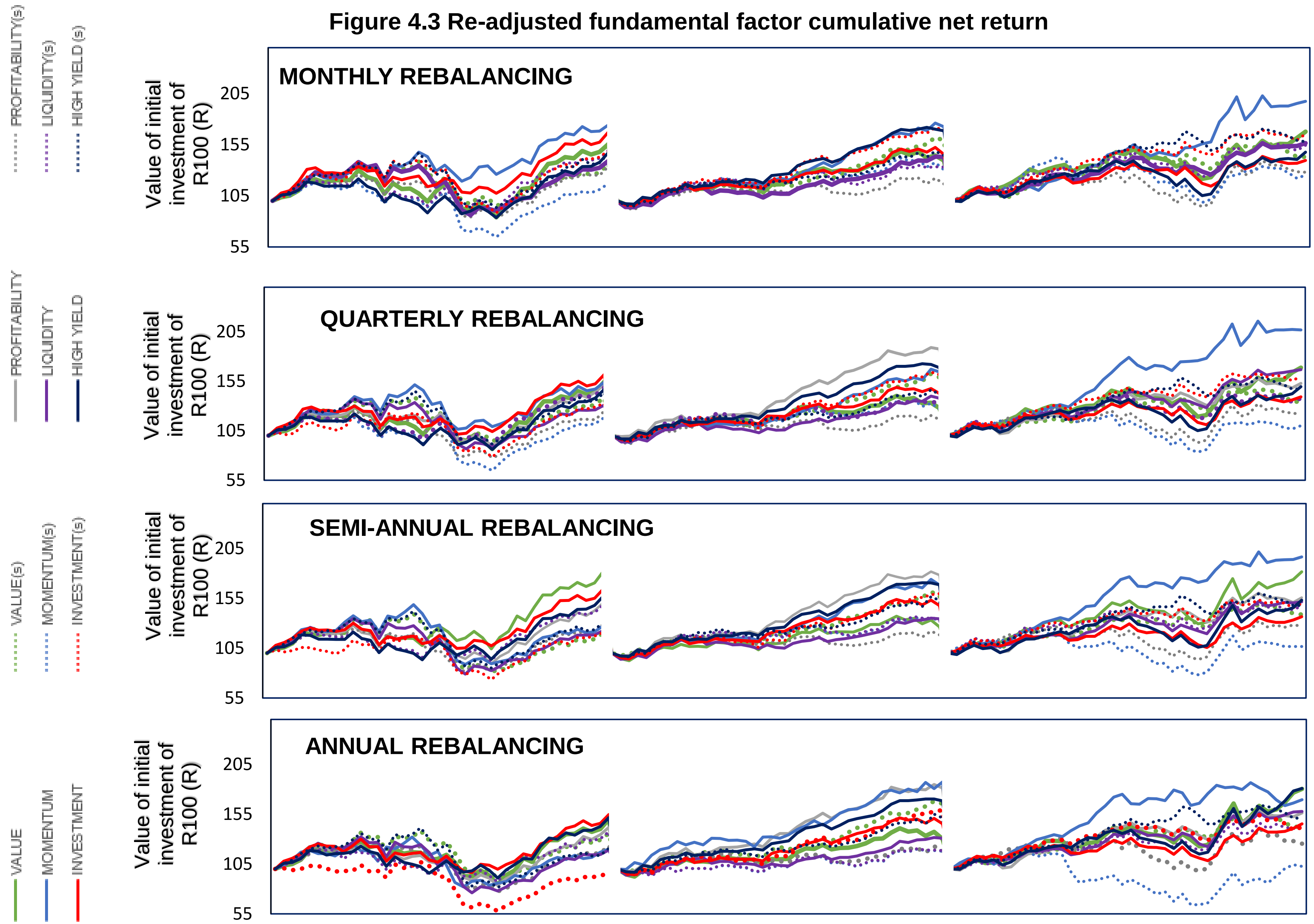
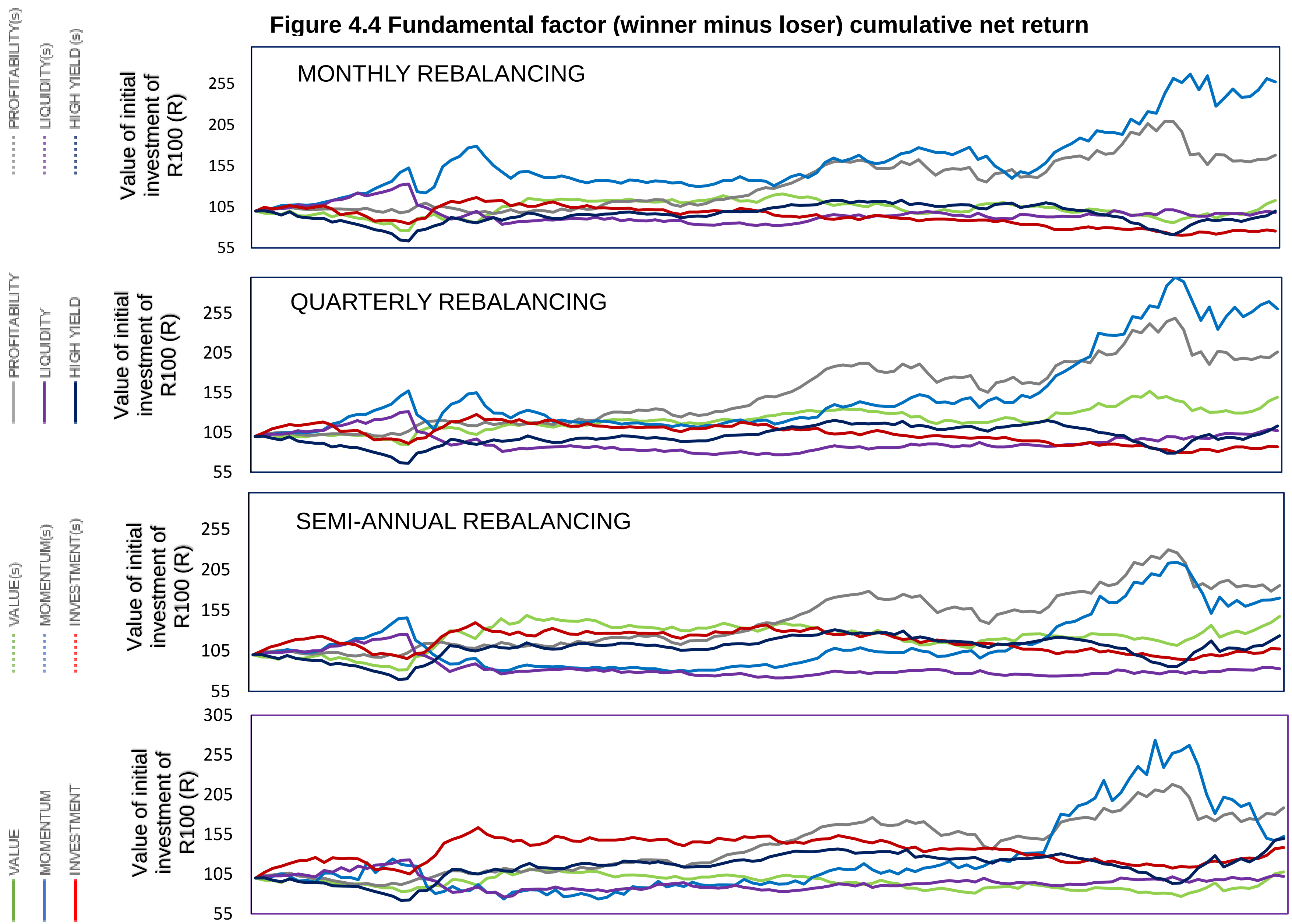


Figure 4.4 Fundamental factor (winner minus loser) cumulative net return



4.3.1 Momentum

Momentum appears to be the best-performing fundamental factor as illustrated in Figures 4.2, 4.3 and 4.4. Figure 4.2 indicates momentum's investment value as portrayed by its ability to correctly identify out- and underperforming stocks over time. This investment value is indicated by the large difference in returns by the respective winner and loser momentum strategies. As the rebalancing frequency decreases, however, the investment value that is held by momentum decreases. This relationship between the investment value of momentum and rebalancing frequency is in line with the expectation that momentum is a short-term indicator (Van Heerden, 2014). Considerable investment value is therefore lost due to the look-back created by only rebalancing much later, therefore only reacting on the new underlying price momentum information over the long term. While short-term market noise is ignored by longer rebalancing period methodologies, momentum outperformed partly due to taking into account the noise in the form of short-term price movements.

Also, momentum outperformed stronger in the market recovery period than in the post-crisis period. This outperformance was expected because price momentum defines the momentum fundamental factor and therefore it will capture short-term market performance persistence. Short-term rebalancing methodologies also indicated investment value in the momentum factor over the financial crisis period. Figure 4.4 shows a negatively correlated relationship between the momentum and other fundamental factors with the exception of profitability. This observation is supported by Figures 4.5 and 4.6. Again, this negative correlation is more significant for shorter rebalancing methodologies than for longer rebalancing periods (see Figure 4.4).

The loser momentum portfolio outperformed the winner portfolio for short periods of time during the financial crisis period, as can be seen in Figure 4.3 (semi-annual and annual rebalancing). This observation indicates an inverse outcome to what the underlying fundamental factor signals, based on price momentum, is expected to produce. Long periods of the loser portfolio outperforming the winner portfolio increased the risk of including that fundamental factor in a smart beta portfolio. The momentum fundamental factor, however, only indicates short periods of reversed signal performance where the loser portfolio outperforms the winner portfolio.

Contrary to what Van Heerden (2014) found, momentum proved to be a relatively stable fundamental factor which was expected to contribute to the outperformance of a smart beta portfolio in the South African market, specifically in combination with shorter rebalancing frequency methodologies. High investment value is held by the momentum fundamental factor. The underlying price momentum variable therefore correctly identified out- and underperforming stocks.

4.3.2 Profitability

Profitability has more stable investment value than momentum, as illustrated in Figure 4.2. At no point in time can it be seen that the loser profitability portfolio outperforms the relevant winner portfolio. In addition, the spread between the winner and loser portfolio is relatively large in comparison to that of the other fundamental factors. The spread is specifically noticeable in the post-crisis period as indicated in Figure 4.3. Profitability is therefore expected to be a significant contributor to the multifactor fund performance.

Profitability is also negatively correlated to the other fundamentals, excluding momentum, as can be seen in Figure 4.4. This negative correlation is supported by Figures 4.5 and 4.6. As all factors are represented to some extent in both multifactor portfolios, a negative correlation allows the portfolio to realise positive returns from profitability and momentum stocks when the other fundamental factors are performing adversely. In times of positive returns realised by the market the opposite is also true, which can be expected to hamper performance. This relationship was expected to decrease volatility in the multifactor portfolios and therefore limits the downside risk of the multifactor portfolio during times of market adversity. This characteristic decreases the risk associated with the resultant multifactor portfolio, which is in line with supporting arguments for smart beta as a passive investment strategy (BlackRock, 2017).

4.3.3 High yield

The high yield factor has little investment value as its signals fail to consistently and correctly identify the out- and underperforming stocks. This weak investment value is clearly evident in Figure 4.3 (monthly rebalancing) where the loser portfolio outperforms the winner portfolio at the start of the crisis periods and only recovers to offer little to no investment value for the rest of the crisis period. The high yield fundamental factor offers some, albeit insignificant, investment value as the winner portfolio again outperformed in the post-crisis period as shown in Figure 4.3 (monthly rebalancing). However, the little investment value derived during this period is reversed in the third period as the winner portfolio again underperformed the loser portfolio. This failure to correctly identify the out- and underperforming stocks is depicted in Figures 4.2 and 4.3 (quarterly and semi-annual rebalancing). However, it seems that as the rebalancing frequency decreases, the investment value held by the high yield factor increases to some extent (Figures 4.2 and 4.3 annual rebalancing).

4.3.4 Liquidity

The relevant winner and loser portfolios do not show any mentionable spread. As no difference between the winner and loser portfolios is observed in both Figures 4.2 and 4.3, liquidity is deemed to have no investment value in the South African environment. The signals vary consistently as the winner portfolio does not consistently offer outperformance above the loser portfolio. The loser portfolio marginally outperformed the winner portfolio during the financial crisis period (see Figure 4.3). However, liquidity mostly offered no investment value as the winner and loser portfolio realised similar returns over time.

Similar to momentum and profitability, liquidity displayed a negative correlation for a short period of time during the crisis period, as illustrated in Figure 4.4. This negative correlation is short-lived, however, and little to no investment value was derived from liquidity thereafter. Liquidity is therefore believed to have limited investment value in the South African environment.

4.3.5 Investment

The expected results of the investment fundamental factor, as defined by Fama and French (2006), differs from the results achieved, as the loser portfolio often outperform ed the winner portfolio. Only with an infrequent annual rebalancing strategy did the low investment winner portfolio outperform the high investment loser portfolio. Figures 4.2 and 4.3 (annual rebalancing) indicate the relatively large spread between the winner and loser portfolios under this rebalancing strategy. The outperformance of the loser investment portfolio, as opposed to that of the relevant winner portfolio, may be caused by an exchange rate effect. Many South African firms bought international assets in the periods following the financial meltdown as a result of the insecurity of the local financial and political environments. Thus, large investments may have generated larger than expected returns due to a weakening Rand. This exchange rate effect possibility was not specifically addressed by Fama and French (2006). The investment factor is therefore considered of little investment value in the South African environment.

As a result, investment value is only expected to be derived from the investment factor where stocks have a longer period to generate outperformance. This waiting period may be because of investments taking time to realise returns. The waiting period was already taken into account to some extent by using a rolling twelve-month look-back period to determine the signals underlying the investment factor. The failure of the investment factor to consistently and correctly identify the out- and underperforming stocks increases the associated risk of including this factor into a multifactor portfolio.

4.3.6 Value

The investment value derived from value as a fundamental factor is unstable. Value offers little to no investment value for the monthly and quarterly rebalancing strategies as shown in Figures 4.2, 4.3 and 4.4 (monthly and quarterly rebalancing).

However, value offers some investment value in combination with a semi-annual rebalancing strategy as shown in Figures 4.2 and 4.3 (semi-annual rebalancing). This investment value is unstable, however, as it diminishes in the post-crisis period where the loser portfolio outperforms the winner portfolio as illustrated in Figure 4.3 (semi-annual rebalancing). The other two periods, however, both demonstrate significant investment value from the value fundamental factor under a semi-annual rebalancing strategy. Yet, both the crisis and market recovery periods contain times of significant negative market performance. The value factor may therefore offer more investment value in times of market upset. This observation is, however, not supported under other rebalancing strategies.

Even with the investment value that may be derived from the value fundamental factor under a semi-annual rebalancing strategy, it still reflects to be an unstable fundamental factor which increases multifactor fund risk. An investment strategy based on the value fundamental factor has been very popular in the South African environment, although this strategy has not outperformed as illustrated in Figure 4.2.

4.3.7 Summary

Profitability is the only fundamental factor that never reverses signals indicated by the loser portfolio outperforming the winner portfolio. It was therefore expected to be less risky to include profitability in a smart beta portfolio than fundamental factors such as value and investment which regularly reverses signals. Momentum seems to be the most likely fundamental factor to drive outperformance. The drivers of return will, however, be further analysed by means of a regression and LASSO analyses and explained later in this chapter. The investment value held by momentum decreases rapidly as the rebalancing methodology changes to less frequent rebalancing. Both momentum and profitability are negatively correlated with the other fundamental factors. Combining the fundamental factors contributes to the diversification of the portfolio to limit downside exposure in adverse market conditions and the associated portfolio risk.

The investment and liquidity fundamental factors are expected to have little to no positive contribution to returns due to their inability to consistently identify outperforming stocks. High yield and value offer more investment value with less frequent rebalancing frequency strategies. However, both failed to consistently derive a possible spread between the respective winner and loser portfolios. The inclusion of these fundamental factors in a multifactor fund therefore offers little to no benefit.

The analysis of the multifactor funds will be discussed next, given the relationships identified which influenced the investment value derived from each fundamental factor. The two multifactor funds were constructed with two varied methodologies. All fundamental factors were represented in each fund, only to different degrees. The resultant portfolios were therefore exposed to all the expected interrelationships of the fundamental factors and the influence of the selected rebalancing strategy.

4.4 MULTIFACTOR FUND PERFORMANCE

The equal-weighted multi factor (EWMF) and the fundamental factor performance history weighted (FFPHW) portfolios were constructed as per the portfolio methodologies described in Chapter 3. It is important to note that the FFPHW portfolio assigned more weight to the signals generated by outperforming the fundamental factor while the EWMF portfolio assigned equal weighting to all signals. Each portfolio, however, only consisted of thirty stocks at any specific point in time. The single-factor performance will be analysed in relation to the multifactor funds' performance in the following section. This section also addresses research Objective II as it considers the portfolio net returns.

4.4.1 Single- and multifactor strategy performance correlation

There are benefits to constructing a multifactor portfolio consisting of fundamental factors with negatively correlated net returns as this offers diversification benefits. Some factors will therefore move similarly to the market while others will be inversely correlated with those fundamental factors and the market. In times of adverse market conditions, the inversely correlated fundamental factors will therefore assist the multifactor portfolio in limiting the downside risk. These diversification benefits, as suggested in Figure 4.4 where fundamental factors move inversely to one another, can be confirmed by means of a correlation analysis. Tables 4.1 and 4.2 and Annexure F indicate the net returns correlation under a monthly and quarterly rebalancing strategy.

As suggested earlier in Figure 4.4, some fundamental factors move inversely to one another. Thus, multifactor portfolios are diversified which limits downside risk in times of market adversity. Similar to the inverse movements of fundamental factors illustrated in Figure 4.4, Tables 4.1 and 4.2 illustrate that momentum and profitability show negative correlation to other single factors. However, momentum is only negatively correlated to the multifactor portfolios with a shorter rebalancing frequency of monthly or quarterly. No correlation is observed between momentum and the EWMF fund with a semi-annual rebalancing strategy (see Annexure F). Profitability remained negatively correlated to both multifactor strategies across all rebalancing strategies.

Table 4.1 Net returns correlation heat map (monthly rebalancing)

	FFPHW	EWMF	VALUE	PROF	MOM	LIQ	INV	HY
FFPHW	1.00							
EWMF	0.84	1.00						
VALUE	0.08	0.25	1.00					
PROF	-0.06	-0.14	-0.16	1.00				
MOM	-0.40	-0.48	-0.34	0.28	1.00			
LIQ	0.19	0.13	-0.20	-0.28	0.15	1.00		
INV	-0.23	-0.12	0.18	-0.08	-0.20	-0.23	1.00	
HY	-0.27	0.03	0.53	-0.01	-0.23	-0.27	0.38	1.00

Table 4.2 Net returns correlation heat map (quarterly rebalancing)

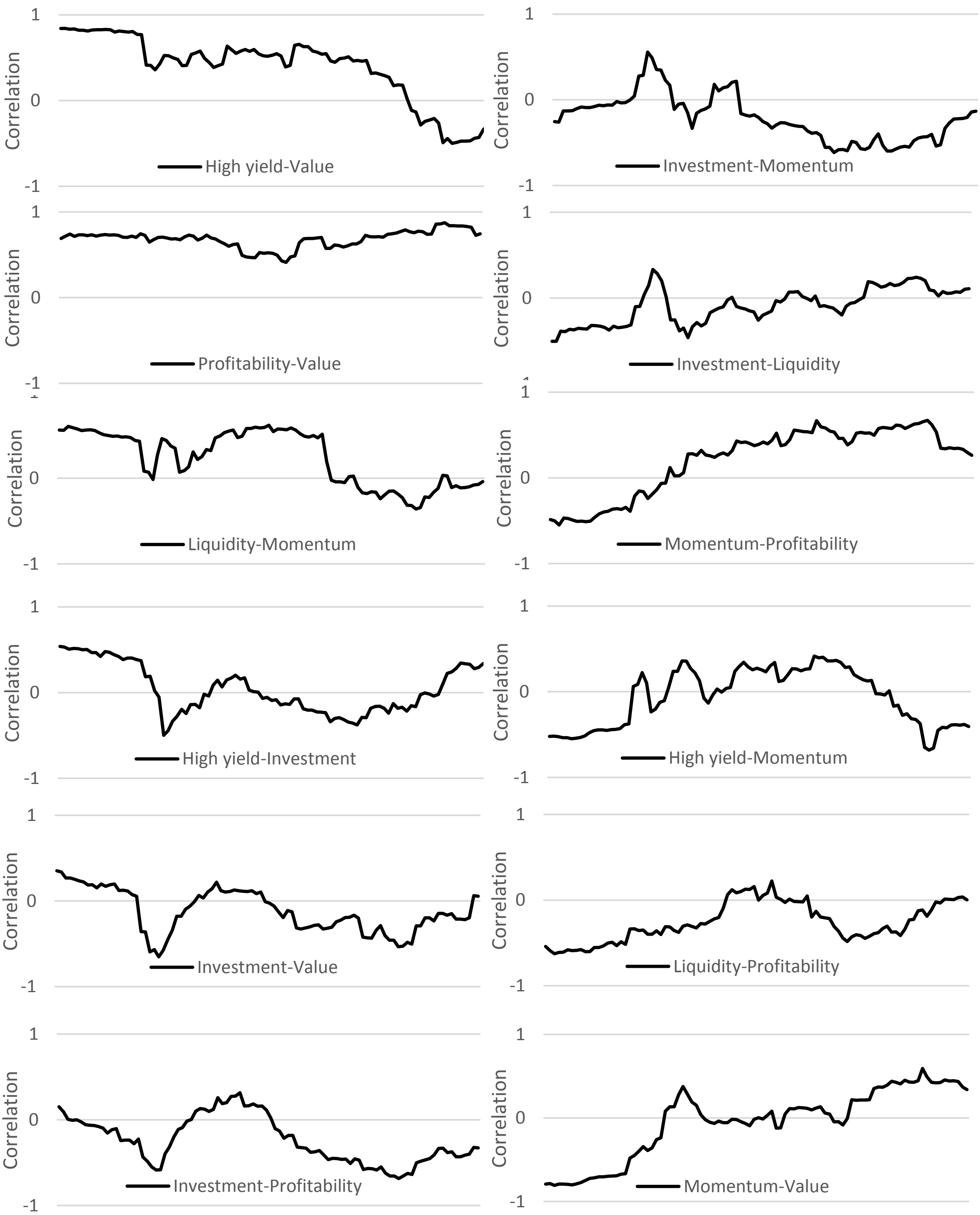
	FFPHW	EWMF	VALUE	PROF	MOM	LIQ	INV	HY
FFPHW	1.00							
EWMF	0.84	1.00						
VALUE	0.23	-0.01	1.00					
PROF	-0.01	-0.31	-0.10	1.00				
MOM	-0.34	-0.19	-0.62	0.30	1.00			
LIQ	-0.19	0.10	-0.53	-0.31	0.42	1.00		
INV	0.00	-0.17	0.35	-0.14	-0.35	-0.23	1.00	
HY	0.26	-0.06	0.67	-0.02	-0.68	-0.44	0.28	1.00

Both the EWMF and the FFPHW are strongly correlated across all rebalancing strategies. Monthly and quarterly rebalancing strategies indicate marginally higher correlation rates. Correlation with the multifactor funds increase as rebalancing frequencies become less frequent. As can be deduced from Table 4.1, monthly rebalancing only offers liquidity and value as relatively correlated single-factor portfolios. As indicated in Annexure F at an annual rebalancing strategy only profitability is noticeably negatively correlated to the EWMF portfolio while only liquidity is somewhat negatively correlated to the FFPHW portfolio.

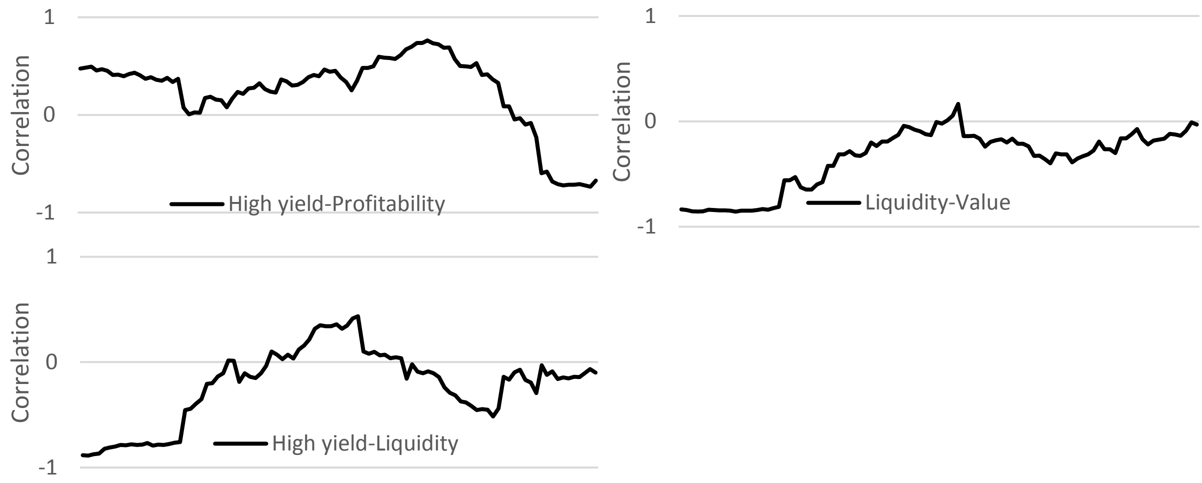
Tables 4.1 and 4.2 display correlations among fundamental factors over the ten-year research period. Figure 4.5 indicates the movement in a rolling twelve-month correlation over the ten-year period. Changes in the correlation of fundamental factors are therefore of value here because it will affect an investor's one-year view.

Figure 4.5 Rolling twelve-month correlation of net returns (quarterly rebalancing)

Panel A Fundamental factors group A



Panel B: Fundamental factors group B



Only profitability and value remain highly correlated throughout the research period when studying the correlation of twelve-month rolling returns, as depicted in Figure 4.5. This positive correlation is not supported by the heat map in Table 4.1. It is however, reflected, in Annexure F, under a semi-annual rebalancing strategy.

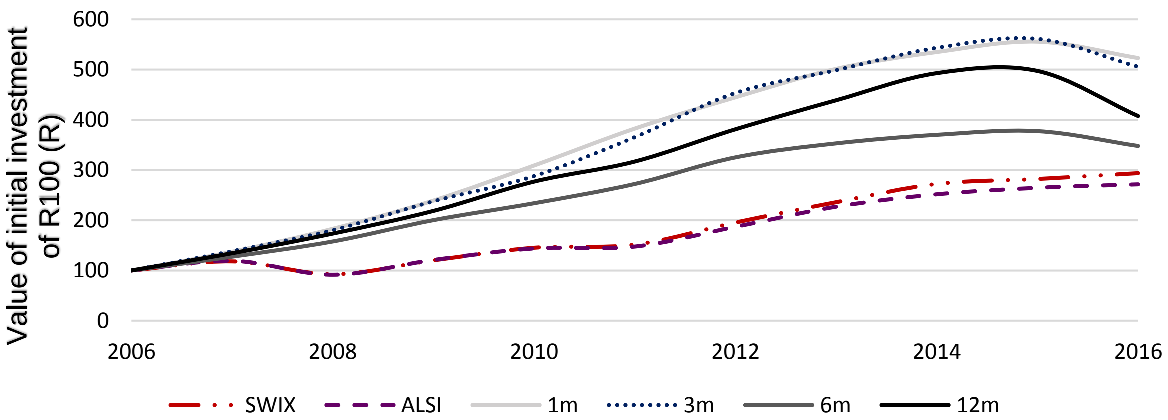
Highly correlated fundamental factors were expected to have a similar relationship in the resultant multifactor portfolios. Should profitability be found to have a positive influence on the multifactor portfolio as a driver of return, value was expected to mimic this relationship. Similarly, negatively correlated fundamental factors were expected to have opposite effects on the resultant multifactor portfolios. These estimations of fundamental factor contribution to multifactor portfolio return can however not be done without relative stability in correlation. As can be seen in Figure 4.5, almost all fundamental factor correlations changed over time, most notably, high yield and value, high yield and profitability and momentum and profitability. High yield specifically seems to have little stability in its correlation with other factors.

Most rolling twelve-month correlations in Figure 4.5 indicate a noticeable period of change in correlation. This change occurred around the middle period of the three respective periods as also referred to in Figure 4.3, namely the post-crisis period. This change is similar to the investment value depletion of many factors observed in the post-crisis period in 2010 and 2014 as displayed in Figure 4.3. The first half of the period represented in Figure 4.5, up until middle to late 2010, indicate consistent correlations among the fundamental factors. The last half of the ten-year period under analysis indicates little consistency. It is important to note that many smart beta funds in South Africa were constructed in 2010 with the information available at the time. The significant changes in the fundamental factor performance, investment value and correlation may explain the slow growth of smart beta as an investment style in South Africa. These funds may thus have been constructed to withstand a different environment that it ended up having to function in.

4.4.2 Equal-weighted multifactor (EWMF) fund

The EWMF multifactor fund after-cost performance as measured against the SWIX and ALSI benchmarks are indicated in Figure 4.6 for various rebalancing frequencies. The applicable trading costs are therefore already taken into account here. Research Objective I is addressed here as net returns are compared to the relevant benchmarks.

Figure 4.6 Cumulative winner EWMF fund net returns



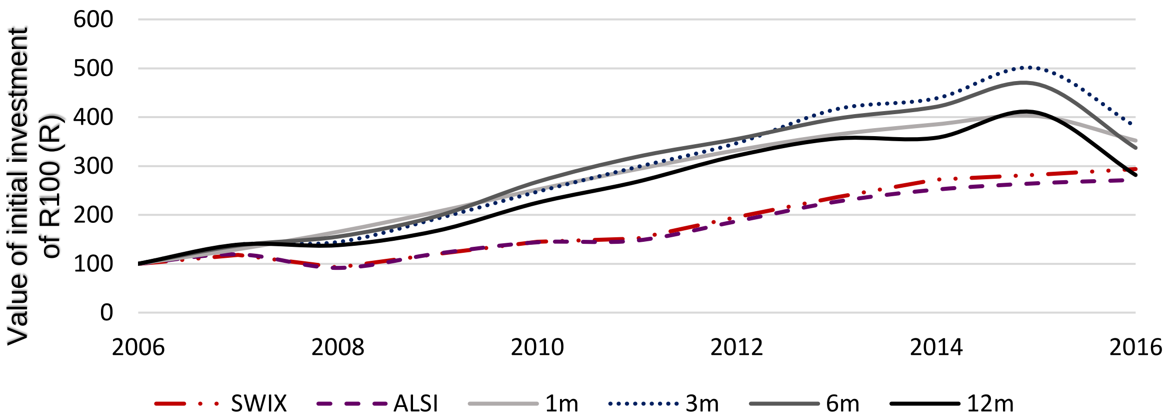
Over the entire research period the EWMF winner portfolio managed to outperform both the benchmarks, namely the SWIX and ALSI, due to the growth in the first five years as indicated in Figure 4.6. However, a downturn in the EWMF portfolio performance is evident in the last years of the research period. The EWMF cumulative returns slowed down in 2012 already, but declined after 2014. Shorter rebalancing strategies such as monthly or quarterly rebalancing proved to consistently outperform the semi-annual and annual rebalancing strategies.

The loser side proved to be of no value in this multifactor portfolio as clearly displayed in Annexure G. A winner portfolio by far outperformed a loser portfolio. However, the underlying fundamental factors managed to identify the underperforming stocks. The underperformance merely failed to produce positive return when incorporated into a loser portfolio strategy. A portfolio following a benchmark may still profit by underweighting stocks with loser signals based on fundamental factors and overweighting stocks with winner signals.

4.4.3 Fundamental factor performance history weighted (FFPHW) fund

The FFPHW multifactor fund's after-cost performance as measured against the SWIX and ALSI benchmarks are indicated in Figure 4.7 for various rebalancing frequencies. Again, trading costs have been deducted from gross performance before comparing the relevant returns to that of the benchmarks.

Figure 4.7 Cumulative FFPHW winner fund net returns



As can be seen in Figure 4.7, the FFPHW also managed to outperform both the SWIX and ALSI benchmarks in after-cost returns due to the cumulative returns realised over the first five-year period. A turning point occurred in 2012 after which the multifactor portfolio struggled to outperform. Large underperformance was recorded for the period after 2014 as the fund lost approximately half of its value while the benchmarks generated positive returns. Again, a quarterly rebalancing strategy proved to be optimal in terms of returns generated. However, it was necessary to analyse the resultant cost of portfolio churn which accompanied each rebalancing strategy before concluding whether any single one could be preferred above the others.

The loser side failed to deliver any value to justify implementing a loser portfolio (see Annexure G). The only period that generated alpha by means of a loser FFPHW strategy was for a short period during the 2008/9 financial crisis. The negative correlation offered by momentum and profitability already protected the multifactor portfolio against periods of financial adversity. The winner portfolio, therefore manages to still outperform during the time of the financial crisis.

Both multifactor portfolios produced positive net returns when implementing a quarterly rebalancing strategy. Table 4.3 indicates cumulative return out- or underperformance compared to the SWIX as well as the after-cost value of an investment made on the first of January 2007 in either benchmark, multifactor funds or single-factor funds.

Table 4.3 also supports the endorsement of a quarterly rebalancing strategy. Short-term rebalancing strategies clearly offer cumulative outperformance over longer-term rebalancing strategies such as semi-annual or annual rebalancing strategies. Due to the additional administration involved in monthly rebalancing, it was expected that quarterly rebalancing would be the optimal rebalancing strategy. This relationship between portfolio churn and rebalancing frequency will be discussed in the following chapter by comparing churn across strategies. Further support for a quarterly rebalancing strategy from a performance perspective is offered in Annexure H by comparing single-factor performance across various rebalancing strategies.

Table 4.3: Active fund performance relative to SWIX

Rebalancing frequency	SWIX	ALSI	EWMF	FFPHW	Value (VAL)	Profitability (PROF)	Momentum (MOM)	Investment (INV)	Liquidity (LIQ)	High yield (HY)
Monthly	R0 (R294, 0%)	R-22 (R272, -0.08%)	R229 (R523, -0.78%)	R58 (R352, -0.2%)	R5 (R298, -0.02%)	R107 (R401, -0.36%)	R316 (R610, -1.08%)	R46 (R340, -0.16%)	R25 (R319, -0.09%)	R68 (R362, -0.23%)
Quarterly	R0 (R294, 0%)	R-22 (R272, -0.08%)	R212 (R506, -0.72%)	R87 (R381, -0.3%)	R46 (R340, -0.16%)	R146 (R440, -0.5%)	R252 (R546, -0.86%)	R31 (R325, -0.11%)	R21 (R314, -0.07%)	R76 (R370, -0.26%)
Semi-annual**ly**	R0 (R294, 0%)	R-22 (R272, -0.08%)	R54 (R348, -0.18%)	R43 (R337, -0.15%)	R133 (R426, -0.45%)	R131 (R425, -0.45%)	R143 (R437, -0.49%)	R44 (R338, -0.15%)	R-34 (R260, -0.12%)	R114 (R408, -0.39%)
Annual**ly**	R0 (R294, 0%)	R-22 (R272, -0.08%)	R114 (R407, -0.39%)	R-12 (R282, -0.04%)	R69 (R363, -0.24%)	R115 (R409, -0.39%)	R84 (R378, -0.29%)	R39 (R333, -0.13%)	R-43 (R250, - 0.15%)	R170 (R464, -0.58%)

Figures 4.8 to 4.11 strengthen the argument in favour of shorter rebalancing period strategies.

Figure 4.8 Cumulative monthly rebalancing fund net returns

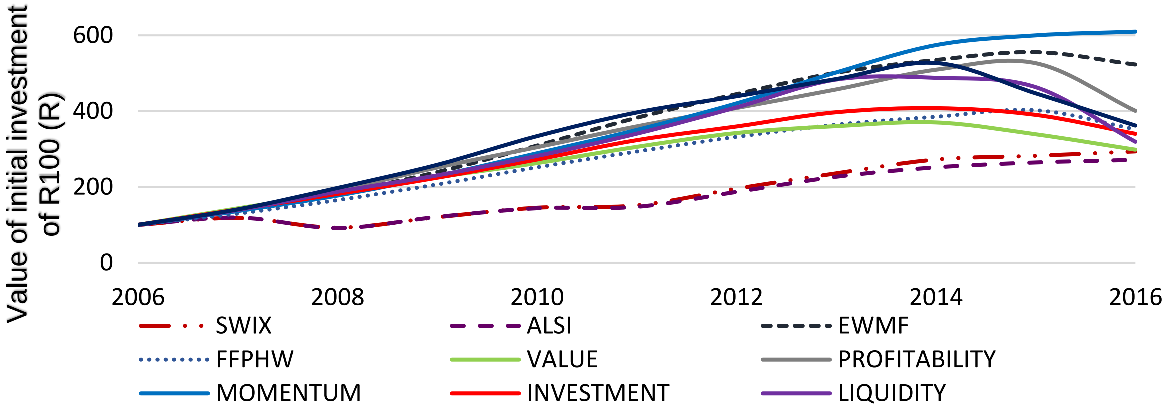
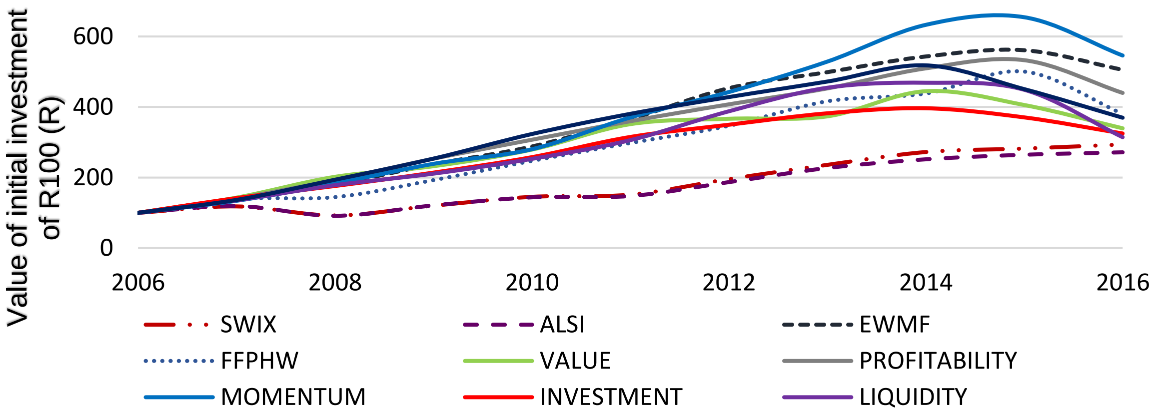


Figure 4.9 Cumulative quarterly rebalancing fund net returns



Semi-annual (see Figure 4.10) and annual rebalancing strategies (see Figure 4.11) indicate cumulative underperformance in the last two years of the ten-year research period. It is also evident that the EWMF strategy outperformed the FFPHW strategy except in the case of a semi-annual rebalancing strategy. This outperformance of the EWMF strategy may be due to the FFPHW factor's inherent nature to give more weighting to the recently outperforming fundamental factor's signals. A significant downturn in the return of these fundamental factors, similar to that of momentum indicated in Figure 4.9, had an increased adverse effect due to the increased factor exposure of the FFPHW portfolio. The discussion of the drivers of return analyses hereafter considers the relationship between the heavy-weighted fundamental factors and their ability then to drive portfolio return.

Figure 4.10 Cumulative semi-annual rebalancing fund net returns

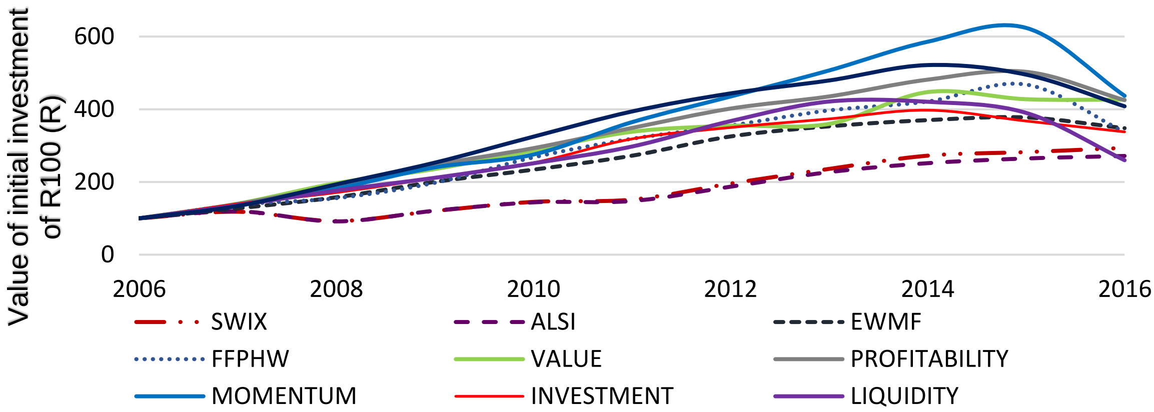
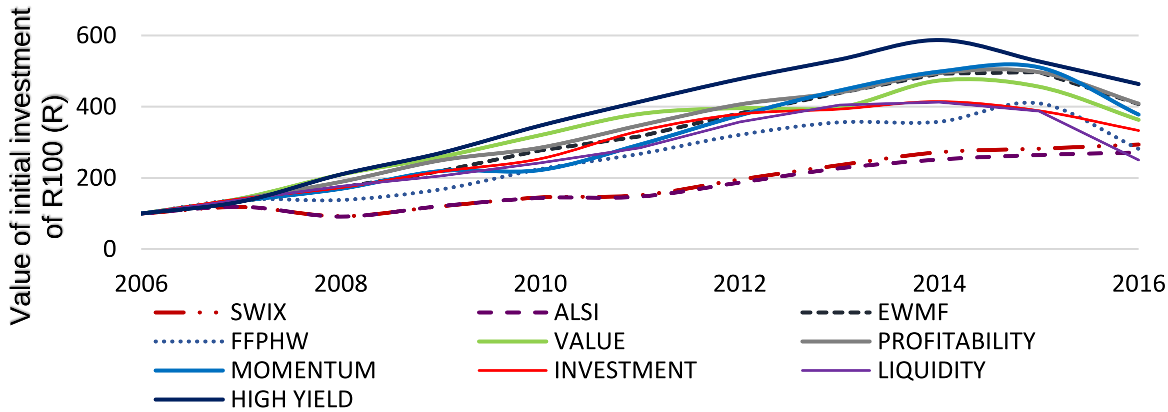


Figure 4.11 Cumulative annual rebalancing fund net returns



The failure of the benchmarks to show a similar slowdown in returns after 2012 to that indicated by the EWMF and FFPHW portfolios in Figures 4.8 to 4.11, may be as a result of the market concentration risk. The ALSI and the SWIX are both heavily weighted in Naspers Limited (JSE: NPN) stocks. While the overall market slowed down after 2012, Naspers grew exponentially over short periods of time. The capitalisation weighted benchmarks therefore increased the weighting of Naspers as the stock price escalated and therefore consistently increased its exposure to the single stock. The large exposure of the benchmarks to the continued growth in Naspers alone therefore protected the benchmark returns from a slow-down.

Annexures G and H support the discussion on portfolio performance and optimal rebalancing frequency as discussed in this chapter. In summary, the following conclusions can be derived from Annexure G and H:

i. Smart beta strategies are optimally managed as long-only strategies. Short selling does not deliver market-adjusted outperformance in the South African environment based on a smart beta strategy.
ii. The underperformance of the short (loser) smart beta funds indicates that the strategies correctly identify undesirable stocks. This information can be used to deliver outperformance in an index- tracking environment by means of factor-tilting.
iii. The quarterly rebalancing strategy consistently delivers better performance than the other rebalancing frequencies across all single-factor portfolios except high yield. The quarterly rebalancing frequency is therefore considered optimal.
iv. The single-factor portfolios outperform both the SWIX and the ALSI benchmarks on a cumulative investment return basis.

The performance indicated in this section was also statistically analysed by means of various *t*-tests to address research Objectives I and II and their related hypotheses (Hypotheses 1 and 2). Both analyses failed to reject their respective null hypotheses ($H_{1:0}$ and $H_{2:0}$). In other words, no statistically significant difference in returns per period between various rebalancing frequencies (research Objective I) or as compared to the benchmarks (research Objective II) were found. The results of the *t*-tests are shown in Annexure I.

4.5 Drivers of return

Regression and LASSO analyses were performed to indicate which fundamental factors managed to drive the return of the relevant multifactor fund. The following analyses therefore addressed research Objective III.

4.5.1 Fundamental factor performance history weighted (FFPHW) fund

The FFPHW fund assigned more weight to outperforming fundamental factors by weighting fundamental factor signals according to their most recent twelve-month performance. It was therefore expected that the factors with increased weights would drive the portfolio returns as they have outperformed in the most recent twelve-month period.

4.5.1.1 Initial weights assigned per factor

Table 4.4 illustrates the frequency of fundamental factors receiving a specific weighting ranging from forty per cent to five per cent in constructing the FFPHW portfolio.

Table 4.4 Incidence of a weight assigned to each fundamental factor

Rebalancing frequency	Weight assigned	40%	25%	15%	10%	5%
Monthly	High yield (HY)	12%	28%	13%	14%	35%
	Profitability (PROF)	24%	23%	13%	18%	23%
	Investment (INV)	0%	3%	33%	25%	39%
	Momentum (MOM)	49%	19%	8%	8%	17%
	Value (VAL)	4%	8%	15%	17%	58%
	Liquidity (LIQ)	12%	21%	19%	19%	30%
Quarterly	High yield (HY)	28%	22%	7%	4%	40%
	Profitability (PROF)	9%	5%	29%	14%	43%
	Investment (INV)	11%	7%	25%	44%	14%
	Momentum (MOM)	44%	18%	4%	11%	23%
	Value (VAL)	5%	19%	24%	16%	37%
	Liquidity (LIQ)	3%	30%	12%	12%	44%
Semi-annual	High yield (HY)	22%	28%	20%	5%	26%
	Profitability (PROF)	14%	12%	11%	28%	37%
	Investment (INV)	7%	18%	18%	39%	19%
	Momentum (MOM)	43%	12%	16%	4%	27%
	Value (VAL)	15%	13%	18%	20%	36%
	Liquidity (LIQ)	1%	19%	18%	14%	48%
Annual	High yield (HY)	22%	28%	19%	5%	26%
	Profitability (PROF)	14%	12%	11%	27%	37%
	Investment (INV)	7%	18%	18%	38%	19%
	Momentum (MOM)	42%	12%	16%	4%	27%
	Value (VAL)	15%	13%	18%	20%	35%
	Liquidity (LIQ)	1%	18%	18%	14%	48%

Note A: The fundamental factors with the highest likelihood of being allocated to the specific weight is allocated in green for each respective rebalancing strategy

Momentum most commonly received the highest weighting of forty per cent followed by high yield. Value and liquidity were the worst-performing fundamental factors as they most commonly received a mere five per cent weighting. Profitability did not receive prominent weights, which is in contrast to what was expected given the investment value held by profitability. Profitability failed to outperform the other fundamental factors over the twelve-month rolling periods which were analysed to determine the weighting scheme and therefore received less weight in the FFPHW portfolio. This weight allocation may be a contributing factor to the EWMF portfolio outperforming the FFPHW portfolio given that significant investment value can be derived from profitability. Profitability offered desirable cumulative net returns as illustrated in the performance analysis section. The reduced exposure to profitability by the FFPHW fund therefore decreased its exposure to the benefits of the profitability fundamental factor.

4.5.1.2 Regression and LASSO analyses

Table 4.5 contains the regression results for each portfolio strategy. The significance F indicates the fundamental factors' ability to explain multifactor portfolio performance.

All the FFPHW regression models were strongly statistically significant in explaining the portfolio return as indicated by the significance $f < .05$. However, low adjusted R-squares were reported. All of the intercepts proved statistically significant. A positive coefficient value suggested that the single-factor moved in relation to the portfolio. A negative coefficient in turn suggested an inverse relationship. For instance, an increase in the profitability factor was expected to result in a decrease in the monthly rebalanced winner FFPHW fund as indicated by the profitability factor coefficient value of -0.44. This negative coefficient value is supported by Figure 4.4 as profitability moved inversely to all other factors except momentum.

Table 4.5 Multifactor portfolio regression

Panel A: Monthly and quarterly rebalancing

REBALANCING STRATEGY	MONTHLY				QUARTERLY			
	LONG (WINNER)		SHORT (LOSER)		LONG (WINNER)		SHORT (LOSER)	
	FFPHW	EWMF	FFPHW	EWMF	FFPHW	EWMF	FFPHW	EWMF
Adjusted R^2	0.1758	0.0330	0.2335	0.3153	0.0909	0.0619	0.2173	0.2759
Significance F	0.0001*	0.1331	0.0000*	0.0000*	0.0096*	0.0386*	0.0000*	0.0000*
Coefficients ^{a}								
Intercepts	1.13%* (3.12)	1.43%* (4.19)	1.28%* (3.29)	1.54%* (4.07)	1.2%* (3.02)	1.46%* (4.24)	1.31%* (3.39)	1.42%* (3.72)
Value (VAL)	0.13 (0.94)	0.24 (1.85)	-0.00 (-0.01)	-0.06 (-0.38)	0.05 (0.24)	0.16 (0.85)	-0.18 (-0.85)	-0.20 (-1)
Profitability (PROF)	-0.44* (-4.45)	-0.09 (-0.97)	-0.13 (-1.22)	-0.49* (-4.72)	-0.33* (-2.08)	-0.32* (-2.29)	0.02 (0.12)	-0.35* (-2.3)
Momentum (MOM)	0.20* (2.42)	0.06 (0.69)	-0.44* (-4.83)	-0.44* (-5.01)	0.25* (2.87)	0.10 (1.31)	-0.44* (-5.12)	-0.39* (-4.64)
Liquidity (LIQ)	0.06 (0.47)	-0.03 (-0.2)	-0.20 (-1.32)	-0.17 (-1.19)	-0.03 (-0.21)	-0.01 (-0.06)	-0.20 (-1.33)	-0.13 (-0.85)
Investment (INV)	-0.28* (-2.1)	-0.09 (-0.69)	-0.38* (-2.59)	-0.48* (-3.41)	-0.21 (-1.38)	-0.12 (-0.92)	-0.33* (-2.25)	-0.43* (-2.98)
High yield (HY)	0.02 (0.18)	0.07 (0.6)	-0.02 (-0.14)	-0.26 (-1.89)	-0.05 (-0.37)	0.24* (2.06)	0.03 (0.22)	-0.20 (-1.58)

Note A: Results indicated as coefficient with t-statistic in brackets. (The critical value at a 5% significance level was 1.98)

Note B: An * indicates statistical significance

Panel B: Semi-annual and annual rebalancing

REBALANCING STRATEGY	SEMI-ANNUALLY				ANNUALLY			
	LONG (WINNER)		SHORT (LOSER)		LONG (WINNER)		SHORT (LOSER)	
	FFPHW	EWMF	FFPHW	EWMF	FFPHW	EWMF	FFPHW	EWMF
Adjusted R^2	0.0917	0.0566	0.1004	0.1563	0.3710	0.2954	0.3550	0.4694
Significance F	0.0093*	0.0490*	0.0060*	0.0003*	0.0000*	0.0000*	0.0000*	0.0000*
Coefficients								
Intercept	1.03%* (2.54)	1.21%* (3.43)	1.22%* (3.25)	1.26%* (3.35)	1.27%* (3.92)	1.45%* (4.62)	1.31%* (4.6)	1.39%* (4.47)
Value (VAL)	0.37* (2.35)	0.31* (2.25)	0.02 (0.15)	-0.09 (-0.63)	0.25* (2.12)	0.23* (2)	0.08 (0.7)	-0.01 (-0.01)
Profitability (PROF)	-0.09 (-0.63)	-0.09 (-0.7)	0.11 (0.86)	-0.35* (-2.6)	0.21 (1.96)	0.08 (0.83)	0.10 (0.96)	-0.33* (-3.3)
Momentum (MOM)	0.20 (1.62)	0.18 (1.69)	-0.33* (-2.94)	-0.29* (-2.56)	-0.32* (-6.53)	-0.29* (-5.98)	-0.35* (-7.17)	-0.36* (-7.61)
Liquidity (LIQ)	0.16 (0.93)	0.13 (0.85)	0.01 (0.04)	-0.02 (-0.15)	0.29* (2.64)	0.25* (2.35)	0.05 (0.43)	0.08 (0.72)
Investment (INV)	-0.33* (-2.2)	-0.20 (-1.49)	-0.20 (-1.47)	-0.40* (-2.88)	-0.25* (-2.12)	-0.24* (-2.13)	-0.28* (-2.41)	-0.47* (-4.17)
High yield (HY)	-0.21 (-1.47)	0.16 (1.27)	0.06 (0.44)	-0.14 (-1.06)	-0.43* (-4.07)	-0.06 (-0.63)	0.15 (1.49)	-0.13 (-1.27)

Note A: Results indicated as coefficient with t-statistic in brackets. (The critical value at a 5% significance level was 1.98)

Note B: An * indicates statistical significance

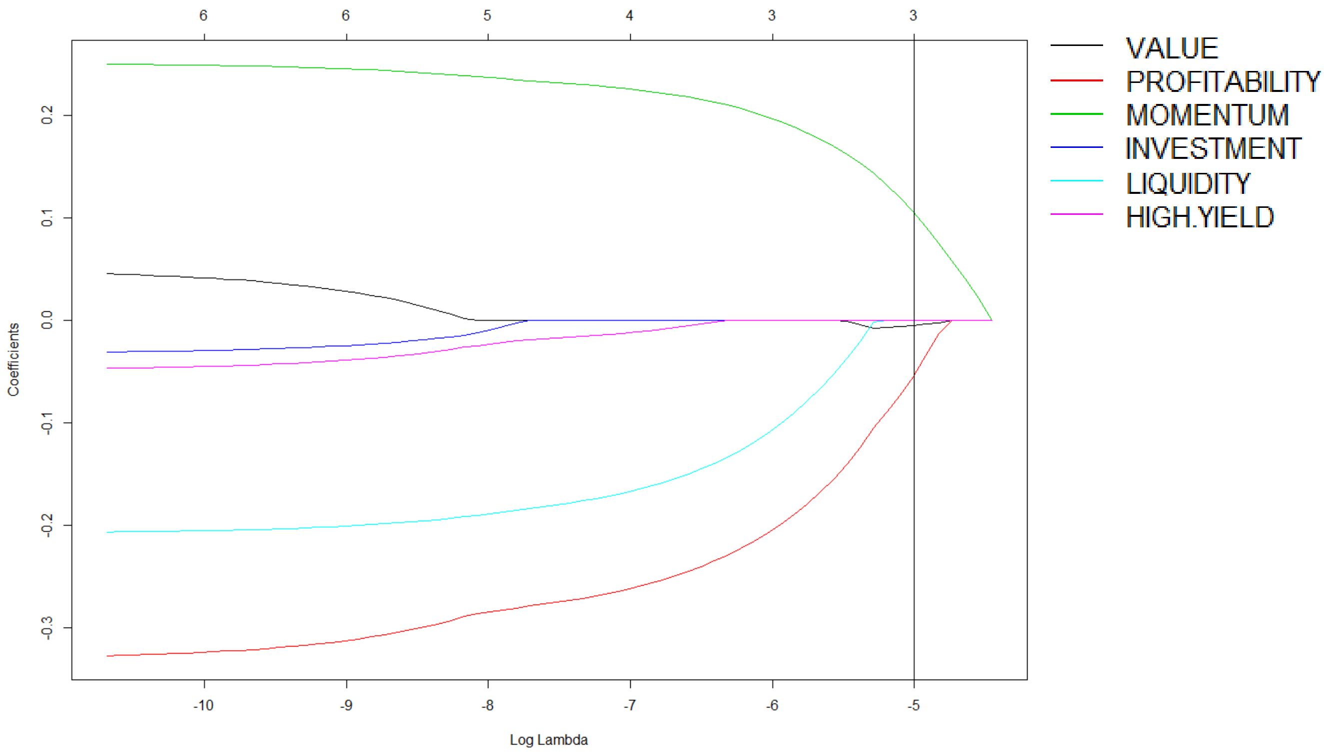
The following conclusions were drawn from Table 4.5:

i. Value only has a statistically significant influence on FFPHW winner portfolio returns for longer rebalancing periods.
ii. Profitability's influence in FFPHW fund return becomes less statistically significant with less frequent rebalancing strategies.
iii. Momentum shows similar statistical significance to that of profitability.
iv. Liquidity and high yield only indicate true investment value under an annual rebalancing strategy.
v. Investment offers statistically significant value in the model for most FFPHW portfolio methodologies.
vi. A semi-annual rebalancing strategy offers little statistically significant drivers of return.
vii. Only value and investment offer statistically significant investment value under a semi-annual rebalancing strategy.
viii. For the preferred quarterly rebalancing strategy only value and momentum move in correlation to the fund returns. An increase of 100 basis points (bps) or one per cent in momentum is expected to yield a 251 bps increase in the FFPHW fund keeping all other factors constant.

Figure 4.12 illustrates the drivers of return based on a LASSO analysis. The factors that are shrunk to null last are the biggest drivers of return. The vertical line in Figure 4.12 indicates the optimal factor inclusion should only three factors be included, namely momentum, then profitability, and lastly value. The top vertical x-axis displays the number of factors remaining in the portfolio as shrinkage occurs.

Momentum therefore was the primary driver of return for the FFPHW winner portfolio followed by profitability and lastly value, as shown in Figure 4.12. This was to be expected as momentum, profitability and value respectively had the three largest coefficient values, as can be seen in Table 4.5. Thus, the LASSO analysis supports the findings based on the regression analysis as displayed in Table 4.5. The drivers of return changed significantly under different rebalancing methodologies as evident in Table 4.5 as well as Annexure J. The LASSO analyses reiterate that profitability's value as a driver of return was lost as the rebalancing frequency decreases. For shorter rebalancing frequencies, namely monthly and quarterly, momentum and profitability seem to typically drive returns of the FFPHW winner portfolio.

Figure 4.12 Quarterly rebalancing FFPHW winner LASSO regression



Fundamental factors with the largest coefficient values that are shown in Table 4.5 offer the best explanation of FFPHW fund returns and should therefore be the first to be included in the portfolio. Table 4.4 supports this explanation of FFPHW fund returns as momentum had the highest weighting. Profitability, however, managed to act as a prominent driver of return even though it was not assigned a higher initial signal weighting under the portfolio methodology as represented in Table 4.4. High yield, however, was regularly allocated the second largest weighting, but failed to drive returns for the FFPHW portfolio. Thus, the initial weighting allocated to a fundamental factor's signals did not seem to materially affect the ability of the fundamental factor to act as a driver of return.

The loser portfolios are primarily driven by momentum. As discussed in the section on performance and indicated in Annexure G, loser portfolios do not seem to be profitable options under the smart beta investment strategy in South Africa.

4.5.2 Equal-weighted multifactor (EWMF) fund

The EWMF fund methodology assigns equal weights to each fundamental factor's signals. The attribution to returns of each fundamental factor in the resultant multifactor portfolio will be discussed next.

4.5.2.1 Regression and LASSO analyses

The regression results in Table 4.5 indicate a limited statistically significant explanation of portfolio returns by fundamental factors included in the model. The significance F is also much larger for EWMF than for FFPHW. The model therefore is less accurate in its aim to identify the drivers of return for EWMF than for FFPHW.

When analysing the drivers of performance, profitability proved to strongly contribute to returns for shorter rebalancing strategies. High yield, momentum and value also had large absolute coefficient values as indicated in Table 4.5. These large coefficient values suggest that these fundamental factors can be expected to be the primary contributors of return for the EWMF winner fund. The LASSO analyses as shown in Figure 4.12 as well as Annexure J, indicated that the primary drivers of return were similar to those suggested by the coefficient values listed in Table 4.5. Here the primary drivers of return for the quarterly rebalancing EWMF winner strategy were high yield, profitability and momentum.

4.6 CONCLUSION

Research Objectives I, II and III were addressed in this chapter. More specifically, the after-cost performance of single- and multifactor portfolios as compared to the relevant benchmarks under varying rebalancing strategies and the drivers of returns were determined. In order to comprehensively address these research objectives, the investment value derived from each individual fundamental factor was determined. Profitability and momentum offer the highest investment value. Shorter rebalancing strategies, however, increase the value that can be derived from the profitability fundamental factor. Investment and liquidity offer little to no investment value in the South African context. Profitability and momentum are often negatively correlated with the other fundamental factors which in turn offer diversification benefits to the multifactor portfolios.

The multifactor portfolios, namely the EWMF and FFPHW, could therefore be analysed given the insights into each individual fundamental factor. Research Objective II was concluded as it was determined that both the EWMF and FFPHW portfolios managed to significantly outperform the SWIX and ALSI benchmarks on an after-cost cumulative basis. This outperformance was primarily driven by performance in the first five years after 2007. The portfolio strategies performed much better prior to 2012. It should be noted that many South African smart beta funds were constructed based on the performance of the fundamental factors pre-2012. This may explain why these funds struggled to outperform the market as smart beta strategy net returns seem to have slowed down after 2012. The benchmark outperformance post-2012 can largely be attributed to the concentration risk in the South African economy. This concentration risk in turn is primarily due to Naspers Limited.

Research Objective I was partially addressed in this chapter. In order to conclude which rebalancing strategy is optimal, an analysis of the effect of portfolio churn was necessary. This discussion on the portfolio churn analysis will be conducted in Chapter 5. The analyses discussed in Chapter 4 suggest that a quarterly rebalancing strategy is optimal. The quarterly rebalancing strategy for both the EWMF and FFPHW portfolios consistently yielded the best returns as compared to other rebalancing strategies.

Finally, research Objective III was addressed in this chapter. Using LASSO and regression modelling it could be determined that momentum, then profitability and lastly value were biggest drivers of return in the winner multifactor portfolios. The loser multifactor portfolio was also primarily driven by momentum.

The classification persistence and resultant portfolio churn which gave effect to the portfolio results as described in this chapter will be analysed and explained in the following chapter.

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CHAPTER 5

CLASSIFICATION PERSISTENCE OF STOCKS

5.1 INTRODUCTION

The philosophy of smart beta as an investment style advocates that stocks should be invested in based on their inherent ability to meet certain fundamental requirements. These requirements are selected based on phenomena that are believed to be present within the equity markets. A trade-off exists between holding a portfolio which is a true replication of the stocks meeting the requirements and the trading costs involved due to consistently trading to ensure the portfolio replicates what the data suggest. This trade-off was examined by comparing classification persistence, portfolio churn and net returns.

Typically, it is expected that increased trading erodes portfolio returns because of the implied costs associated with the increased portfolio churn. However, if the smart beta portfolio successfully identifies outperforming stocks, the associated trading costs might not have a material effect on the net returns. In other words, the portfolio should manage to outperform due to its timely replication of what the data suggest the portfolio holdings should be.

The support of a more frequent rebalancing strategy, specifically a quarterly rebalancing strategy, suggests that a marginal benefit of return is realised. More investment value is therefore realised by trading more often at the loss of additional trading costs. Chapter 4 showed that shorter rebalancing strategies outperform longer rebalancing strategies. A quarterly rebalancing strategy is therefore appropriately suggested as the optimal strategy. This finding suggests that the smart beta portfolio has the ability to outperform with higher portfolio churn. Here, trading costs were included and already proved that they do not erode outperformance. The portfolio churn and the classification persistence of stocks are further explored and discussed in this chapter. At the conclusion of this chapter, fund fact sheets will be presented containing summarised information from Chapters 4 and 5 – information that would be typically requested by a potential investor.

5.2 PORTFOLIO CHURN

Portfolio churn here refers to the annual trades as a percentage of portfolio value that is required to rebalance the portfolio to the desired weights. A quarterly rebalancing strategy will therefore rebalance four times a year. The sum of these four rebalancing activities produces the annual churn rate. As a result, it is possible for a portfolio to have an annual churn of more than 100 per cent. Table 5.1 illustrates the sum of the churn per single- and multifactor portfolio, per calendar year. Research Objective IV is addressed in this section by analysing portfolio churn and its relationship with net returns.

Table 5.1 Heat map of annual churn per portfolio (quarterly rebalancing)

	FFPHW	EWMF	VAL	PROF	MOM	LIQ	INV	HY
2007	0.34	0.34	0.35	0.32	0.38	0.33	0.39	0.27
2008	0.79	0.64	0.56	0.77	0.79	0.88	0.58	0.50
2009	0.35	0.30	0.44	0.34	0.38	0.41	0.36	0.30
2010	0.28	0.27	0.27	0.31	0.38	0.37	0.31	0.24
2011	0.25	0.28	0.31	0.26	0.29	0.30	0.30	0.26
2012	0.27	0.28	0.33	0.27	0.29	0.32	0.36	0.26
2013	0.28	0.27	0.39	0.32	0.30	0.35	0.37	0.28
2014	0.33	0.31	0.42	0.31	0.34	0.39	0.37	0.27
2015	0.40	0.39	0.47	0.41	0.42	0.54	0.39	0.48
2016	0.50	0.54	0.47	0.39	0.56	0.51	0.48	0.46

As can be seen in Table 5.1, annual portfolio churn increased during the 2008/9 financial crisis. However, the increased trading was short-lived as stability resumed in 2010. An overall increase in churn due to lower factor classification persistence was observed for 2015 and 2016. As expected, increased market volatility persisted during these years, leading to increased portfolio churn.

Classifying stocks according to high yield consistently produced a lower portfolio churn than when using the other fundamental factors. Investment and liquidity typically produce higher churn than the other fundamental factors in the same year. The inclusion of the investment and liquidity fundamental factors contributes little investment value as indicated in Chapter 4. The increased churn of investment and liquidity strengthens the argument to not include these fundamental factors when constructing a smart beta fund in the South African context.

It is expected that a more frequent rebalancing strategy translates to an increase in churn. Some market noise is disregarded, by not trading on those market movements, as the rebalancing strategy becomes less frequent. By implementing a more frequent rebalancing strategy, short-lived signals, which may indicate that trading is necessary, may be acted upon before prices mean-revert. Acting upon these signals more frequently will increase the total annual churn. Hypothesis 4 ($H_{4:0}$) and Proposition 1 investigates this expected relationship, namely that a more frequent rebalancing strategy's annual churn will be more than its less frequent counterpart. Tables 5.2 and 5.3 and Figure 5.1 address Hypothesis 4 as it in turn addresses research Objective IV.

The first value indicated in each block of Table 5.2 is the difference in average churn of the two rebalancing strategies. As it is always the less frequent strategy minus the more frequent strategy, for instance semi-annual (6m) average annual churn minus quarterly (3m) average annual churn, a negative difference indicates a higher average churn for the more frequent strategy. All the possible combinations indicate a negative difference and therefore a higher average churn for the more frequent rebalancing strategies. The second value indicated in each block of Table 5.2 is the t-statistic.

Eighty per cent of all *t*-tests as indicated in Table 5.2 are statistically significant. The monthly-quarterly, monthly-annually and quarterly-annually comparisons are statistically significantly different for all portfolios. The quarterly-semi-annually and semi-annually-annually comparisons are least likely to be statistically significantly different. The null hypothesis for Hypothesis 4 ($H_{4:0}$) is therefore rejected because a difference in portfolio churn for different rebalancing strategies is observed.

Table 5.2 Difference in churn of rebalancing intervals (Longer period minus shorter period)

Portfolio	Rebalancing frequency	1m	3m	6m
FFPHW	3m	-28.78%*		
		(-3.85)		
	6m	-37.24%*	-8.46%	
		(-5.17)	(-1.22)	
	12m	-46.84%*	-18.07%*	-9.61%*
		(-8.27)	(-3.38)	(-1.94)
EWMF	3m	-25.2%*		
		(-4.28)		
	6m	-44.22%*	-19.03%*	
		(-7.07)	(-3.13)	
	12m	-41.72%*	-16.52%*	2.50%
		(-8.91)	(-3.73)	-0.51
Value (VAL)	3m	-24.75%*		
		(-5.16)		
	6m	-34.75%*	-10%*	
		(-7.09)	(-2.46)	
	12m	-42.18%*	-17.43%*	-7.43%*
		(-9.44)	(-4.92)	(-2.02)
Profitability (PROF)	3m	-25.16%*		
		(-3.41)		
	6m	-34.06%*	-8.90%	
		(-4.63)	(-1.35)	
	12m	-42.66%*	-17.5%*	-8.60%
		(-7.3)	(-3.63)	(-1.79)
Momentum (MOM)	3m	-28.55%*		
		(-3.93)		
	6m	-38.36%*	-9.80%	
		(-5.06)	(-1.35)	
	12m	-48.95%*	-20.4%*	-10.6%*
		(-8.72)	(-3.97)	(-1.9)
Liquidity (LIQ)	3m	-27.42%*		
		(-3.37)		
	6m	-39.32%*	-11.90%	
		(-5.2)	(-1.68)	
	12m	-48.09%*	-20.67%*	-8.77%*
		(-7.63)	(-3.61)	(-1.8)
Investment (INV)	3m	-26.1%*		
		(-5.25)		
	6m	-36.94%*	-10.83%*	
		(-7.48)	(-2.99)	
	12m	-45.51%*	-19.4%*	-8.57%*
		(-10.31)	(-6.77)	(-3.06)
High yield (HY)	3m	-25.97%*		
		(-4.55)		
	6m	-34.18%*	-8.21%*	
		(-6.18)	(-1.85)	
	12m	-39.32%*	-13.35%*	
		(-7.49)	(-3.26)	

Note A: * indicates a statistically significant difference between the churn of the two rebalancing strategies for a one-tailed *t*-test.

5.2.1 Relationship between portfolio churn and net returns

Given the rejection of the null Hypothesis 1 ($H_{1:0}$), namely that different rebalancing strategies offer the same returns, it is expected that a more frequent rebalancing strategy will lead to increased portfolio churn. As portfolio churn incurs trading costs, it can be postulated that increased churn would lead to decreased after-cost (net) returns. An inverse relationship, or negative correlation, between net returns and portfolio churn for each portfolio is therefore expected. Table 5.3 shows the relationship between the net return and churn.

Table 5.3 Correlation of annual net return and churn (Quarterly rebalancing)

	Portfolio	Net return
Churn	FFPHW	-49.75% (-1.62)
	EWMF	-19.86% (-0.57)
	Value (VAL)	-10.32% (-0.29)
	Profitability (PROF)	25.93% (0.76)
	Momentum (MOM)	-6.69% (-0.19)
	Liquidity (LIQ)	-7.86% (-0.22)
	Investment (INV)	-14.75% (-0.42)
	High yield (HY)	-33.88% (-1.02)

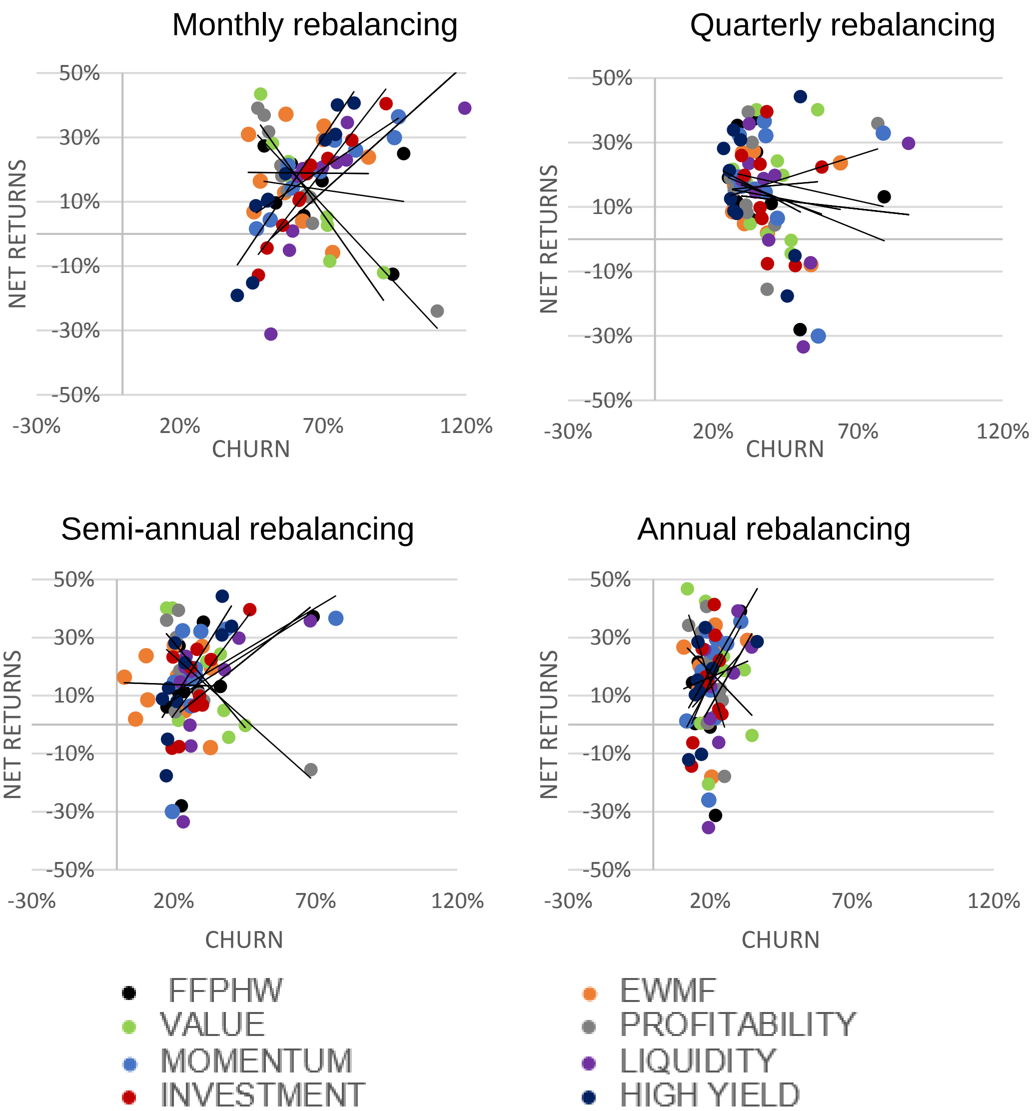
Note A: * indicates a statistically significant correlation
Note B: The first value indicated is the correlation between net return and portfolio churn. The second value in brackets indicates the relevant p-value

Only the profitability fundamental factor shows a positive relationship between portfolio churn and net returns. The other fundamental factors indicate negative correlations to varying extents. As the portfolio churn is considerably larger (in excess of 100 per cent at times) than the portfolio net return data, it is to be expected that perfect positive or negative correlation of 1 and -1 respectively, is unlikely. None of the correlations are statistically significantly different from zero (in other words, there is no correlation).

Only the fundamental factor performance history weighted (FFPHW) and high yield exhibit a considerable negative correlation between portfolio churn and net returns. Notably, profitability indicates a moderately positive correlation. No strong negative or positive correlations between portfolio churn and net returns were, however, present. This lack of a strong correlation is reiterated by the scatterplots in Figure 5.1.

In Figure 5.1, the linear trend lines indicate the relevant direction and trend of each portfolio's plots. The trend lines offer deeper insight into the relationship between net returns and portfolio churn. A horizontal line indicates no correlation, a downward sloping line indicates an inverse relationship (negative correlation) and an upward sloping line indicates a positive correlation between net returns and churn.

Figure 5.1 Relationship between net returns and churn across rebalancing periods



No single rebalancing strategy seems to have a coherent correlation between portfolio churn and net returns per calendar year. A number of individual fundamental factor portfolios, however, indicate strong correlations for the different rebalancing strategies:

i. First, value had a correlation of -0.94 for monthly rebalancing;
ii. Profitability exhibited a strong negative correlation (for a monthly, semi-annual and annual rebalancing strategy) of -0.94, -0.78 and -0.69 respectively;
iii. Oddly high yield exhibited a strong positive correlation for a monthly, semi-annual and annual rebalancing strategy of 0.93, 0.79 and 0.63 respectively;
iv. Investment exhibited a strong positive correlation for a monthly and semi-annual rebalancing strategy of 0.97 and 0.69 respectively; and
v. The quarterly rebalancing strategy correlations, as indicated by Table 5.3, were unique as both profitability and high yield which typically displayed a strong negative and positive correlation indicated a contradictory correlation for a quarterly rebalancing strategy.

Based on the trends in Figure 5.1, portfolio churn is expected to be a function of rebalancing frequency. The expected inverse relationship between portfolio churn and net returns, however, could not be concluded. Increased churn is therefore not necessarily an indicator of poor performance, but shows that smart beta strategies that trade more frequently benefit despite the resultant trading costs. The benefit of trading due to these signal changes shows the investment value of the fundamental factors. A less frequent rebalancing strategy as a result does not outperform its more frequent counterparts as supported by the portfolio performance analysis discussed in Chapter 4. Similar to the performance analysis, the portfolio churn analysis also supports the use of a quarterly rebalancing strategy.

5.3 CLASSIFICATION PERSISTENCE

Smart beta portfolios and the related churn that need to rebalance are essentially a product of the classification persistence of the chosen fundamental factors. The classification persistence of both mixed portfolios as well as the six chosen fundamental factors was investigated. In other words, a stock's probability of remaining classified as a winner (buy), neutral (not bought, sold or held) or a loser (sell) signal within each single- or multifactor portfolio was investigated for look-back periods of four, five or six months respectively. This section therefore addresses research Objectives V, VI and VII.

5.3.1 Multifactor portfolios classification persistence overview

Table 5.4 illustrates the classification persistence of stocks in the two multifactor portfolios. A high probability (strong classification persistence) indicates more stability in the signals and therefore less trading is expected to be necessary.

Table 5.4 Probability of multifactor portfolio stock persisting with its current classification for following month

Group	Portfolio	Four-month look-back period	Five-month look-back period	Six-month look-back period
Winner (long)	FFPHW	0.74	0.76	0.77
	EWMF	0.67	0.66	0.65
	Difference	0.07	0.10	0.12
Neutral	FFPHW	0.80	0.83	0.85
	EWMF	0.66	0.67	0.68
	Difference	0.14	0.16	0.17
Loser (short)	FFPHW	0.81	0.83	0.84
	EWMF	0.86	0.86	0.88
	Difference	-0.05	-0.03	-0.04

Note A: Table 5.4 reads as follows: A stock in the FFPHW portfolio that has been classified as a buy (winner) signal for four consecutive months has a 74 per cent probability of remaining a winning stock for a fifth month.

Stocks in the winner FFPHW portfolio remained in the portfolio for longer than in the winner portfolio of the equal-weighted multifactor fund (EWMF) as indicated by the higher probabilities. The FFPHW winner portfolios consistently delivered stronger classification persistence than the EWMF portfolio as illustrated by Table 5.4. It can therefore be assumed that the FFPHW portfolio is more stable than the EWMF portfolio for winner portfolios. The EWMF portfolio classification persistence was more stable than the FFPHW for the loser portfolios. Furthermore, the classification persistence became stronger with the increased look-back period. Stocks that have been strong buy signals were likely to remain so. The same holds true for the loser (sell signals) portfolios.

The classification persistence was stronger for the overall loser portfolios than for the winner portfolios. Stocks therefore tend to struggle more to consistently be the best in meeting the 'good' requirements than meeting the 'bad' requirements. It can therefore be expected that the winner portfolio will have more churn than the loser portfolio. When using a two-factor ANOVA to measure the difference between the winner and loser portfolios, the winner EWMF portfolio churn was statistically significantly larger than that of the loser EWMF portfolio at a five per cent significance level ($p < .05$). The FFPHW portfolio shows no statistically significant difference in churn between the winning and losing portfolios (p-value of 0.21). The classification persistence difference between the winner and loser EWMF portfolio of 0.19 is substantially larger than the same difference of 0.07 for the FFPHW (see Table 5.4). The portfolio churn therefore differs more significantly between the winner and loser EWMF than between the counterpart FFPHW portfolios.

5.3.1.1 Classification persistence model sample inclusion

The incorporation of a four-, five- and six-month look-back period when studying classification persistence necessarily excludes the short-lived changes in winner (buy), neutral, or loser (sell) signals. The aim of the classification persistence study is, however, to identify the probability of stocks which have already persisted for at least four months to persist for another month. Stocks consistently changing signals are not considered in the classification persistence study. These stocks are still considered and included when constructing the multifactor portfolios. Table 5.5 provides the percentage of the total sample that meets the requirements for the classification persistence model minimum look-back period.

Table 5.5 Stock classification changes considered in the classification persistence incorporating look-back periods

MONTHS PERSIS-TED	FFPHW	EWMF	VALUE	PROF	MOM	LIQ	INV	HY
< 4	51.87%	63.44%	32.74%	19.23%	54.91%	47.29%	20.07%	28.72%
≥ 4	48.13%	36.56%	67.26%	80.77%	45.09%	52.71%	79.93%	71.28%

Only stocks that have persisted for more than four months are taken into account by the model to determine further classification stability. Momentum, liquidity and the multifactor portfolios specifically have a low sample inclusion in the model. The signal movements in these portfolios therefore tend to be short-lived and will not be taken into account for the classification persistence model. The short-lived tendency of signals is already an indication of classification persistence. The signals of the multifactor portfolios and momentum tend to be more short-lived than that of the other portfolios. Lower classification persistence is therefore expected for the momentum and multifactor portfolios as their sample inclusion, in other words the percentage of stocks that have persisted for more than four months, is much lower in comparison to those of the other portfolios.

The classification persistence model therefore only determined the probability of stocks that have already persisted for a period in excess of four months to continue persisting in their specific category. As a result, strong classification persistence of the single-factor portfolios does not necessarily signal strong multifactor portfolio classification persistence. Single-factor portfolios such as profitability, investment and high yield had much higher inclusion rates than the multifactor portfolios. It is expected that the stricter requirements for the multifactor portfolios are the cause of the lower inclusion rates. In other words, stocks have to consistently meet fewer requirements to receive winner classification in the single-factor portfolios, such as profitability, than it does in the multifactor portfolios. The increased competition between stocks to meet all the necessary requirements to classify as a winner in the FFPHW or EWMF portfolios therefore decreased the longevity of signals. The lower classification persistence due to increased competition is expected to persevere in the classification model results as will be discussed in the subsequent sections.

5.3.2 Classification persistence over time

Given that classification persistence is the measure of the probability of a stock to remain classified as a winner (buy), neutral or a loser (sell) position for a specified period of time, it is to be expected that volatile market conditions will influence the classification persistence. Times of excessive financial uncertainty and volatility (such as the 2008/9 financial crisis) are known to disrupt financial markets. This increased volatility in turn may lead to weaker classification persistence, as illustrated in Table 5.6.

Table 5.6 Single-factor portfolio classification persistence over time (2007–2016)

Panel A: four-month look-back classification persistence in the winner portfolio

	VAL	PROF	MOM	LIQ	INV	HY
2007	0.96	0.96	0.75	0.96	0.90	0.95
2008	0.89	0.96	0.64	0.96	0.92	0.94
2009	0.91	0.96	0.51	0.97	0.91	0.92
2010	0.90	0.97	0.74	0.95	0.91	0.96
2011	0.93	0.97	0.62	0.96	0.92	0.95
2012	0.95	0.97	0.68	0.94	0.93	0.97
2013	0.92	0.98	0.67	0.95	0.92	0.94
2014	0.95	0.98	0.69	0.94	0.90	0.96
2015	0.93	0.96	0.68	0.92	0.91	0.96
2016	0.93	0.97	0.58	0.97	0.90	0.96

Panel B: four-month look-back classification persistence in the loser portfolio

	VAL	PROF	MOM	LIQ	INV	HY
2007	0.94	0.96	0.74	0.97	0.90	0.97
2008	0.90	0.94	0.71	0.94	0.92	0.94
2009	0.92	0.96	0.54	0.95	0.92	0.91
2010	0.91	0.92	0.57	0.93	0.86	0.95
2011	0.95	0.95	0.67	0.95	0.94	0.97
2012	0.95	0.98	0.72	0.95	0.94	0.96
2013	0.94	0.96	0.66	0.97	0.92	0.96
2014	0.93	0.97	0.71	0.96	0.92	0.96
2015	0.96	0.97	0.76	0.96	0.91	0.98
2016	0.92	0.96	0.55	0.97	0.91	0.96

Classification persistence does not significantly weaken or strengthen for varying economic cycles. A slight (statistically insignificant) change in the classification persistence from 2008 to 2009 is still observed. However, the overall impression is that market conditions have little to no influence on the portfolio classification persistence. This lack of influence may be due to the look-back period that was taken into account. As the stocks were already required to meet the portfolio requirements for four, five or six months respectively in order to be taken into account. Stocks with strong classification persistence are therefore expected to remain stable. A stock's ability to consistently meet the single-factor portfolio's requirements is therefore a good indication of its future classification stability.

Of the six selected fundamental factor portfolios only momentum showed weak classification persistence. Momentum has proved to be a significant driver of returns, but momentum also had the weakest classification persistence across all single-factor portfolios. The trade-off between trading costs, which result from weak classification persistence and portfolio return generated by the fundamental factor, comes into question again. Given that momentum managed to act as a major driver of return net of costs, the trade-off again leans toward a true replication of fundamental factor signals, which in turn acted as the driver of single-factor performance. Weak classification persistence was therefore not an indication of fundamental factor underperformance. By including momentum it is beneficial in the multifactor portfolios (see Chapter 4), and excluding the fundamental factor due to its weak classification persistence would hinder portfolio performance. The multifactor portfolio's classification persistence is evident in Table 5.7.

Table 5.7 Multifactor portfolio classification persistence over time (2007–2016)

	WINNERS		LOSERS	
	FFPHW	EWMF	FFPHW	EWMF
2007	0.75	0.61	0.76	0.87
2008	0.74	0.66	0.73	0.85
2009	0.64	0.59	0.78	0.83
2010	0.73	0.63	0.91	0.89
2011	0.71	0.63	0.84	0.89
2012	0.84	0.72	0.89	0.82
2013	0.77	0.64	0.80	0.86
2014	0.77	0.68	0.80	0.86
2015	0.74	0.73	0.78	0.88
2016	0.59	0.71	0.68	0.83

The winner portfolios of both multifactor portfolios show weaker classification persistence compared to single-factor portfolios. Stocks have to consistently satisfy several fundamental factor requirements to be eligible for a winner or loser classification within a multifactor portfolio. It is therefore to be expected that because of the increased competition between stocks to be classified as a winner or loser, thus being in the 30 best-performing or worst-performing stocks respectively, will decrease the classification persistence of these portfolios.

The multifactor portfolios have more signals competing to be selected as the best-performing 30 stocks and therefore be classified as a winner signal. The signals were therefore more short-lived than that of the single-factor portfolios as illustrated in Table 5.5. The classification persistence model for the FFPHW and EWMF winner portfolios as a result only considered 48.13 per cent and 36.56 per cent of the total sample, respectively. The other 51.87 per cent and 63.44 per cent represent signals that have failed to persist for a minimum of four months. The FFPHW and EWMF portfolios incorporated these signals when constructing the portfolios, whereas the classification persistence tests ignored these short-lived signals. The strong classification persistence of single-factor portfolios therefore do not necessarily implicate strong multifactor classification persistence owing to the increased competition.

The classification persistence for a five- and six-month look-back period differs very slightly from that of a four-month classification persistence. No statistically significant difference between these probabilities could be proved (Refer to Annexure K for the five- and six-month look-back classification persistence results). Hypothesis 5 ($H_{5:0}$) and the corresponding research Objective V was therefore rejected as the classification persistence of stocks did not significantly differ for varying look-back periods of four, five and six months, respectively.

5.3.3 Classification persistence of the winner stocks in comparison to the loser stocks

The aforementioned discussion on multifactor portfolio classification persistence suggests that winner portfolios are less stable than their respective loser portfolios. Table 5.8 illustrates the results of the two-factor ANOVA tests at a 5 per cent significance level. The difference between the winner and loser portfolios (winner minus loser) is indicated for each calendar year. Each difference indicated in Table 5.8 is the average difference between the winner and loser portfolios across all six single-factor and two multifactor portfolios. In addition, the p-value of a two-factor ANOVA comparing the winner and loser portfolios for each look-back period is indicated in Table 5.9.

Table 5.8 Difference between winner and loser portfolio classification persistence (two-factor ANOVA results)

	Four-month look-back period	**Five-month look-back period**	**Six-month look-back period**
2007	-0.03	-0.03	-0.05
2008	-0.03	-0.04	-0.05
2009	-0.05	-0.04	-0.06
2010	-0.02	0.01	0.00
2011	-0.06	-0.07	-0.09
2012	-0.03	-0.03	-0.03
2013	-0.04	-0.03	-0.03
2014	-0.03	-0.01	0.01
2015	-0.05	-0.04	-0.05
2016	-0.02	-0.05	-0.06
p-value	0.0000*	0.0001*	0.0001*

Note A: * indicates statistical significance

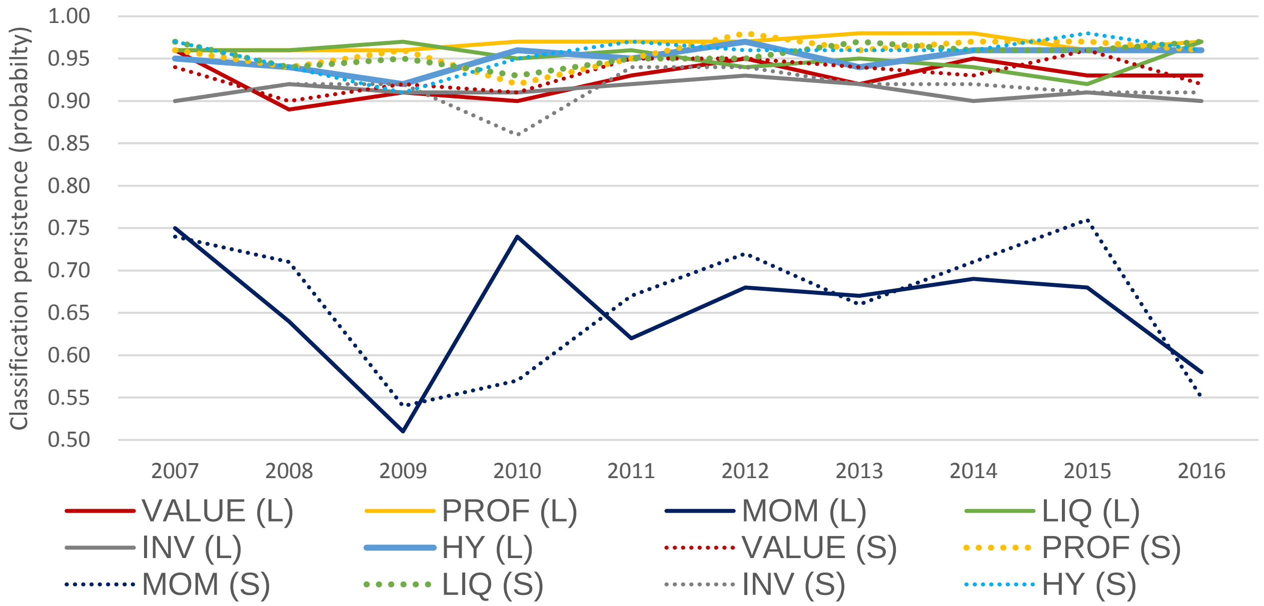
The following conclusions are drawn from Table 5.8:

i. A statistically significant difference between the classification persistence of winner and loser stocks existed as indicated by the relevant p-values;
ii. The difference in stability between the winner and loser portfolios was most evident at a four-month look-back period;
iii. On average the losing portfolio indicated larger probabilities and therefore stronger classification persistence; and
iv. The winner (buy-side) portfolio was thus less stable than the loser portfolio and was therefore expected to require more trading.

Figure 5.2 illustrates this difference between the winner and loser portfolios' classification persistence over time. While Table 5.8 indicates only the overall difference over the ten-year research period, Figure 5.2 offers more insight into the movement of the different portfolio classification persistence over time and in relation to each other.

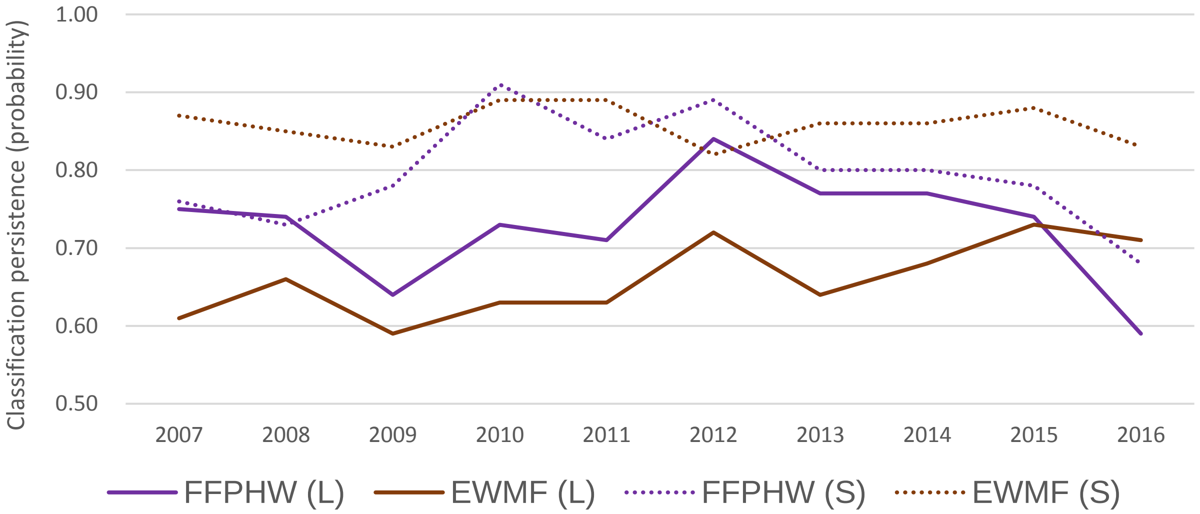
Figure 5.2 Classification persistence of winners versus losers (four-month look-back period)

Panel A: Single-factor portfolios



Note A: 'L' refers to a long (winner) portfolio, while 'S' refers to a short (loser) portfolio.

Panel B: Multifactor portfolios



Note A: 'L' refers to a long (winner) portfolio, while 'S' refers to a short (loser) portfolio

Figure 5.2 indicates that the majority of the fundamental factors maintained a strong, stable classification persistence, similar to that suggested in Table 5.6. Momentum and the two multifactor portfolios, however, showed weaker classification persistence and more volatility in this regard.

Both Table 5.8 and Figure 5.2 indicated that the loser portfolio was more stable than the winner portfolios. The EWMF portfolio specifically indicated a substantial difference between the winner and loser classification persistence.

5.3.4 Sector classification persistence

Each fundamental factor assigns winner or loser classifications to different stocks based on the ability of the stock to meet the specific requirements set by each fundamental factor. Certain fundamental factors are therefore more likely to include stocks from specific sectors than others. For instance, the value fundamental factor is unlikely to include stocks from a growth-dominated industry such as the technology sector. Figure 5.3 offers insight into the sector allocation of the multifactor portfolios as context for thoroughly addressing research Objective VII.

Figure 5.3 Multifactor portfolio sector allocation area charts

Panel A: EWMF portfolio sector allocation

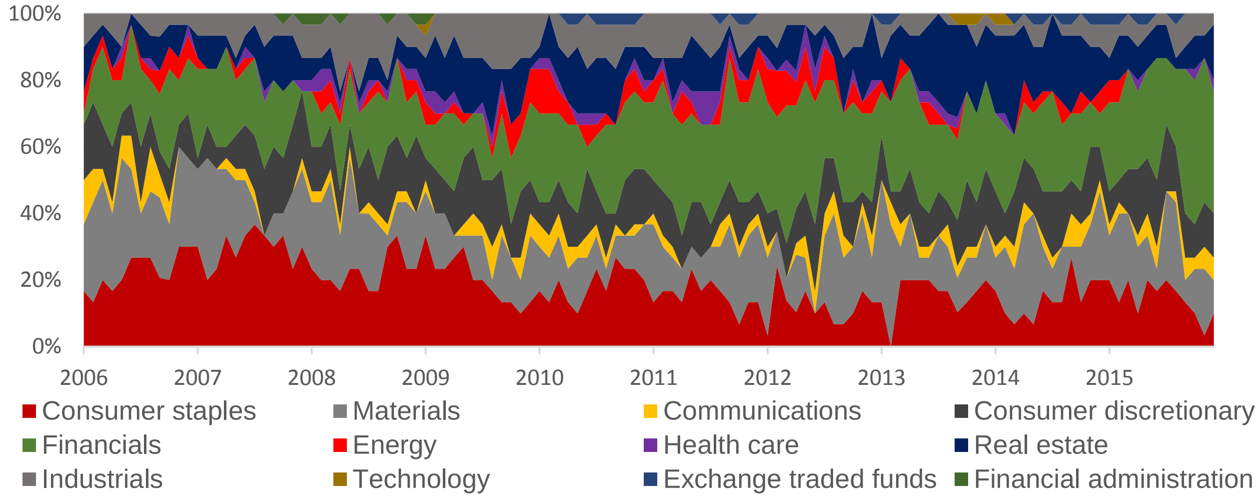
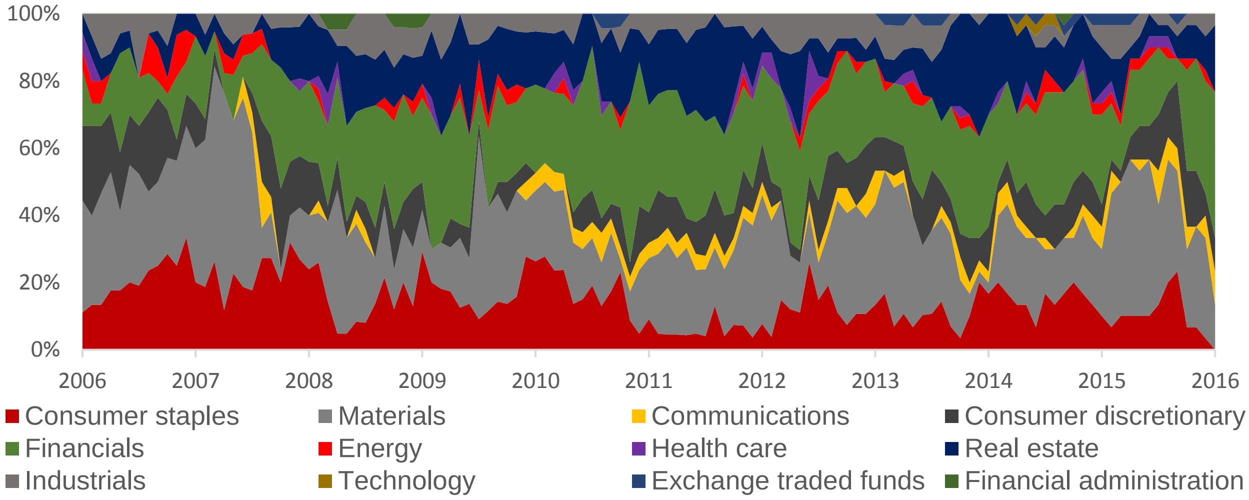


Figure 5.3 illustrates that the FFPHW portfolio shows more volatility in sector allocation than the EWMF portfolio. This can be expected as the FFPHW portfolio assigned more weight to outperforming fundamental factors and stocks in one sector is expected to have similar characteristics. Thus, it is likely that certain fundamental factors are dominated by a few sectors. Both multifactor portfolios were heavily weighted in the financials, consumer staples, materials, and real estate sectors. The EWMF portfolio

Panel B: FFPHW portfolio sector allocation



is also concentrated in the consumer discretionary sector, more so than the FFPHW portfolio.

The classification persistence of the sectors with the largest presence in the eight respective portfolios were measured and are displayed in Table 5.9. The classification persistence observed for each sector over the research period is indicated for each look-back period in Table 5.9. The p-values of single factor ANOVA tests, used to determine whether there is a difference in the classification persistence across sectors, is also shown in Table 5.9. Research Objective VII was addressed in this table as it determines the difference between classification persistence observed for each market sector.

No pattern per sector is noticeable. Table 5.9 shows that the classification persistence is strong across the different market sectors.

Table 5.9 Classification persistence per sector (*t*-test for difference results for winner portfolio)

Sector	Four-month look-back period	Five-month look-back period	Six-month look-back period
Materials	0.85	0.86	0.86
Real estate	0.83	0.84	0.88
Financials	0.86	0.88	0.88
Consumer staples	0.83	0.83	0.82
Industrials	0.85	0.79	0.91
Consumer discretionary	0.86	0.84	0.84
Communication	0.85	0.91	0.93
Energy	0.89	0.90	0.90
Healthcare	0.86	0.86	0.86
Technology	0.94	0.96	0.95
ANOVA p-value	0.99	0.94	0.80

Note A: * indicates statistical significance

The single factor ANOVA tests determined that no statistically significant difference is present between any sectors for a four-, five- and six-month look-back period. Table 5.9 also illustrates the relevant p-values at a 5 per cent significance level. Research Objective VII and its corresponding null Hypothesis ($H_{7:0}$) can therefore not be rejected as no difference between sector classification persistence could be found.

5.4 Relationship between classification persistence and portfolio churn

Weak classification persistence is expected to lead to increased portfolio churn, resulting in increased trading costs and therefore decreased net returns. In other words, an inverse relationship between classification persistence and portfolio churn is expected. Table 5.10 indicates the relationship observed between classification persistence and portfolio churn. This table therefore addressed research Objective IV and proposition 1.

Table 5.10 Correlation between classification persistence and portfolio churn for the winning portfolios

		CLASSIFICATION PERSISTENCE		
	Portfolio	Four-month look-back period	Five-month look-back period	Six-month look-back period
CHURN	FFPHW	0.09	0.22	0.26
	EWMF	-0.77	-0.67	-0.70
	Value (VAL)	0.15	0.13	0.06
	Profitability (PROF)	0.31	0.31	0.20
	Momentum (MOM)	0.34	0.36	0.27
	Liquidity (LIQ)	0.33	0.02	0.11
	Investment (INV)	0.04	0.21	0.57
	High yield (HY)	-0.54	-0.51	-0.16

Table 5.10 indicates that most portfolios do not show the inverse relationship (negative correlation) expected between classification persistence and portfolio. The only winner portfolios with the expected negative correlation was the EWMF and high yield portfolios. The EWMF portfolio specifically indicated a strong negative correlation between portfolio churn and classification persistence. The EWMF portfolio had weak classification persistence in comparison to other portfolios, as seen in Table 5.6. The expected relationship between weak classification persistence and net returns was evident for the winner EWMF portfolio. The strongest negative correlation between portfolio churn and net returns is observed in Table 5.3 for the EWMF portfolio. The inverse relationship illustrated in both Tables 5.3 and 5.10 therefore indicates that weak classification persistence does have a negative effect on net returns. To a lesser extent this was also the case for the high yield portfolio. This inverse relationship was not observed for the other winner portfolios. All portfolios are therefore not subject to the negative effect of weak classification persistence on net returns.

Table 5.11 illustrates the relevance of this negative effect of weak classification persistence on net returns on the loser portfolios.

Table 5.11 Correlation between classification persistence and portfolio churn for the loser portfolios

		CLASSIFICATION PERSISTENCE		
	Portfolio	Four-month look-back period	Five-month look-back period	Six-month look-back period
CHURN	FFPHW	-0.55	-0.44	-0.27
	EWMF	-0.2	0.04	0.09
	Value (VAL)	-0.50	-0.55	-0.59
	Profitability (PROF)	0.05	0.02	0.03
	Momentum (MOM)	0.05	0.23	0.22
	Liquidity (LIQ)	0.16	0.31	0.31
	Investment (INV)	-0.22	-0.35	-0.43
	High yield (HY)	-0.30	-0.47	-0.54

The loser portfolios showed the negative effect of weak classification persistence on net returns more prominently than the winner portfolios. The loser FFPHW, value, investment and high yield portfolios indicated moderately negative correlation. These portfolios all showed positive correlation between portfolio churn and net returns (see Annexure L). Weak classification persistence therefore does not necessarily suggest decreased net return even though it increases portfolio churn for losing portfolios. Annexure L illustrates the relationship between portfolio churn and net returns for the losing portfolios.

A number of individual portfolios indicated a moderately negative correlation between portfolio churn and classification persistence. However, no strong relationship across all winner and loser portfolios existed. The winning EWMF portfolio specifically indicated a relationship between classification persistence and net returns. The larger portfolio churn, as a result of weak classification persistence, increased trading costs and therefore diminished net returns. The winning high yield portfolio supports this finding. However, no other winner or loser portfolio showed this relationship between portfolio churn and the resultant net returns. Proposition 1 (research Objective IV) could therefore not be concluded for all portfolios. The winner portfolios are less likely to be subjected to the negative effect of weak classification persistence on net returns than the loser portfolios. The EWMF portfolio was the most sensitive to this relationship between classification persistence and portfolio churn. The increased portfolio churn, however, does not necessarily diminish returns because of increased trading costs. Weak classification persistence after a stock has already persisted for at least four months therefore has little influence on the net returns of the portfolio.

5.5 CONCLUSION

This chapter addressed research Objectives IV, V, VI and VII by studying the portfolio churn and classification persistence of stocks. The effect of classification persistence and portfolio construction implications were measured by studying the resultant after-cost returns.

Research Objective IV were addressed by measuring portfolio churn and its relationship with classification persistence and net returns. The null hypothesis of Hypothesis 4 ($H_{4:0}$: $\mu_1 = \mu_3 = \mu_6 = \mu_{12}$) was rejected as more frequent rebalancing strategies were proved to be subject to more portfolio churn than less frequent strategies. Weak classification persistence for some portfolios, the EWMF portfolio in particular, led to increased portfolio churn. However, the increased portfolio churn, due to weak classification persistence, did not diminish after-cost returns as the relationship between net returns and classification persistence was not significantly negative. Notably, the profitability portfolio indicated positive correlation between portfolio churn and net returns indicating that more trades improved after-cost portfolio performance. Similar to the performance analysis discussed in Chapter 4, the portfolio churn analysis also supports implementing a quarterly rebalancing strategy.

A classification persistence analysis was conducted to address the three remaining research objectives, namely research Objectives V, VI and VII. Single-factor portfolios were found to have strong classification persistence once a stock has already persisted for at least four months. This classification persistence did not become significantly stronger or weaker when a longer look-back period of respectively five and six months was incorporated. Only the momentum portfolio showed weaker classification persistence. The weaker classification persistence of momentum is in line with the short-lived nature of price momentum that influence the momentum fundamental factor.

The winner portfolios proved to be significantly less stable than the loser portfolios. The null Hypothesis 6 ($H_{6:0:}\, \varphi_L = \varphi_S$) was rejected as a difference was clear between the classification persistence of the long and short portfolio. So-called ‘good’ stocks (winners) are therefore less likely to remain ‘good’, while ‘bad’ stocks (losers) are more likely to remain ‘bad’.

Research Objective VII or Hypothesis 7 ($H_{7:0}$) was addressed by studying the classification persistence of stocks across market sectors. The multifactor portfolios were found to be heavily weighted in the financial, material and consumer staples sectors. However, portfolio sector allocation proved to have no influence on the classification persistence of stocks. No statistically significant difference between classification persistence of stocks across sectors were found. The null Hypothesis 7 ($H_{7:0}$: $\varphi_{s1} = \varphi_{s2} = \varphi_{sn}$) could therefore not be rejected.

Finally, the relationship between classification persistence, portfolio churn and net returns were investigated (research Objective IV). Remarkably, the EWMF portfolio was firstly, subjected to the negative effect of classification persistence on portfolio churn, secondly, showed the second weakest classification persistence among the portfolios, and lastly, has the highest portfolio churn among the portfolios. However, the EWMF portfolio also outperformed the benchmarks more than any other portfolio (see Chapter 4). The implication on the portfolio of rebalancing therefore offers more benefit than it incurs losses due to trading costs. Increased trading costs due to more trading and based on smart beta fundamental factor signals, do not necessarily diminish net returns. Also, weak classification persistence after a stock has already persisted for at least four months has little influence on the net returns of the portfolio.

The following fund fact sheets provide an insight into the multifactor funds as would be typically requested by a potential investor. These fund fact sheets therefore summarise selected information from Chapters 4 and 5.

FUNDAMENTAL FACTOR PERFORMANCE HISTORY WEIGHTED FUND (FFPHW)

Fund information as at 31 December 2016

WHAT IS THE FUND'S INVESTMENT POLICY?

This fund employs a smart beta investment philosophy. Stocks are selected from the JSE TOP 100 based on market capitalisation. The smart beta investment style takes into account six fundamental factors, namely value, profitability, momentum, liquidity, investment and high yield. A quarterly rebalanced fundamentally weighted strategy is used to determine which stocks to include in the FFPHW strategy.

WHAT IS THE FUND'S OBJECTIVE?

This fund seeks to offer consistent market-adjusted outperformance by investing in South African JSE listed stocks. It is benchmarked against the SWIX (shareholder weighted index). The fund is appropriate for investors with high risk appetite.

HOW LONG SHOULD INVESTORS REMAIN INVESTED?

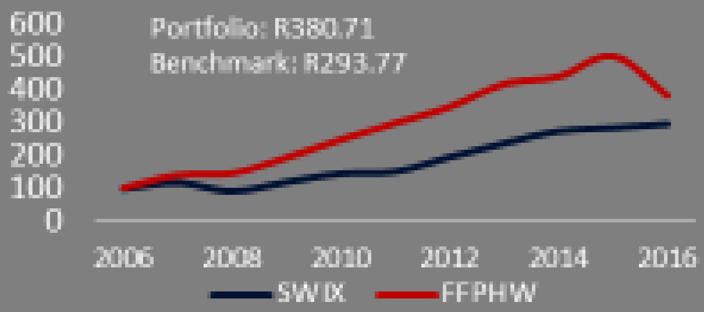
It is recommended that investors with a long investment horizon consider the FFPHW fund. A minimum of 5-7 years investment is recommended.

GENERAL FUND INFORMATION

SECTOR ALLOCATION

PERFORMANCE AND RISK STATISTICS

GROWTH OF R100 INVESTMENT SINCE INCEPTION (10 years)



Launch Date	**1 January 2007**
Benchmark	Shareholder Weighted Index (SWIX)
Investment Minimum	ZAR10,000 lump sum or ZAR5,000/month

Disclaimer:
Past performance does not guarantee or predict future results.

PERFORMANCE FOR VARIOUS PERIODS

	Fund	Benchmark	Active Return
Since Launch (HPR)	280.7%	193.7%	86.9%
Since Launch (annualised)	14.3%	11.4%	2.9%
Latest 3 years (annualised)	-2.9%	7.6	-10.5%
Latest 1 year (annualised)	-23.9%	4.1%	-28.1%

RISK STATISTICS SINCE INCEPTION

	Fund	Benchmark
Annualised Deviation	17.9%	15.4%
Return per unit risk (SHARPE RATIO)	0.14%	0.01%
Maximum Annual Gain	39.0%	29.9%
Maximum Annual Drawdown	-21.7%	-23.9%
Average Annual Portfolio Churn	37.9%	-

FUNDAMENTAL FACTOR PERFORMANCE HISTORY WEIGHTED FUND (FFPHW)

Fund information as at 31 December 2016

WHAT IS THE FUND'S INVESTMENT POLICY?

This fund employs a smart beta investment philosophy. Stocks are selected from the JSE TOP 100 based on market capitalisation. The smart beta investment style takes into account six fundamental factors, namely value, profitability, momentum, liquidity, investment and high yield. A quarterly rebalanced fundamentally weighted strategy is used to determine which stocks to include in the FFPHW strategy.

WHAT IS THE FUND'S OBJECTIVE?

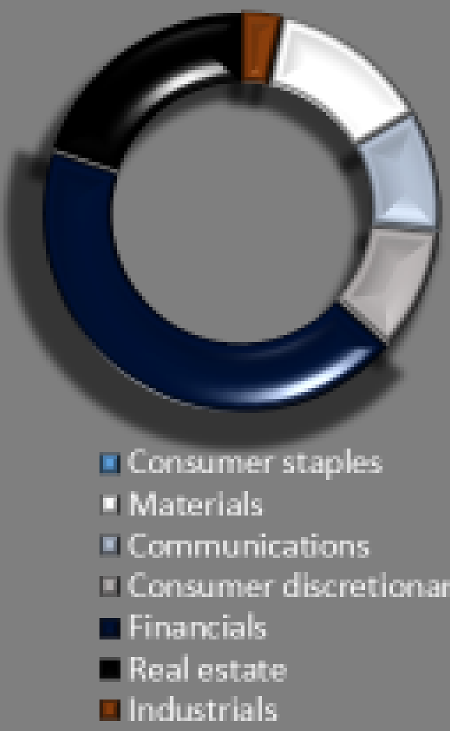
This fund seeks to offer consistent market-adjusted outperformance by investing in South African JSE listed stocks. It is benchmarked against the SWIX (shareholder weighted index). The fund is appropriate for investors with high risk appetite.

HOW LONG SHOULD INVESTORS REMAIN INVESTED?

It is recommended that investors with a long investment horizon consider the FFPHW fund. A minimum of 5-7 years investment is recommended.

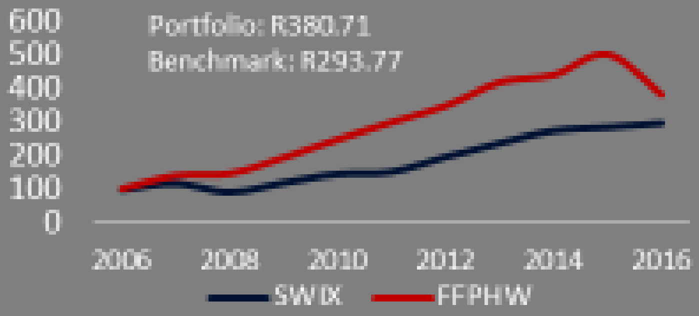
GENERAL FUND INFORMATION

SECTOR ALLOCATION



PERFORMANCE AND RISK STATISTICS

GROWTH OF R100 INVESTMENT SINCE INCEPTION (10 years)



Launch Date	1 January 2007
Benchmark	Shareholder Weighted Index (SWIX)
Investment Minimum	ZAR10,000 lump sum or ZAR5,000/month

Disclaimer:
Past performance does not guarantee or predict future results.

PERFORMANCE FOR VARIOUS PERIODS

	Fund	Benchmark	Active Return
Since Launch (HPR)	280.7%	193.7%	86.9%
Since Launch (annualised)	14.3%	11.4%	2.9%
Latest 3 years (annualised)	-2.9%	7.6	-10.5%
Latest 1 year (annualised)	-23.9%	4.1%	-28.1%

RISK STATISTICS SINCE INCEPTION

	Fund	Benchmark
Annualised Deviation	17.9%	15.4%
Return per unit risk (SHARPE RATIO)	0.14%	0.01%
Maximum Annual Gain	39.0%	29.9%
Maximum Annual Drawdown	-21.7%	-23.9%
Average Annual Portfolio Churn	37.9%	-

CHAPTER 6

CONCLUSIONS, LIMITATIONS AND RECOMMENDATIONS

6.1 INTRODUCTION

In emerging markets such as the South African market, investors are exposed to more risk compared to their counterparts in developed markets. However, the increased risk exposure also presents opportunities to profit for the proficient investor. Several investment styles have been developed to offer market outperformance over time. Smart beta has recently gained popularity globally as an investment philosophy capable of offering attractive risk-adjusted returns (BlackRock, 2017). This investment style initially introduced by Fama and French (1993), uses a combination of established market fundamentals such as value, profitability and liquidity to generate outperformance.

The South African market, however, has been slow to adapt to this global trend. This resistance to smart beta is possibly due to the uncertainty surrounding the unique challenges faced when running a smart beta fund in an emerging market environment. Globally there has been concern that smart beta funds lack transparency (Cox, 2014). Another cause for concern is the possible cost implications of trading in a shallower market. This study therefore investigated the portfolio construction implications of a smart beta strategy that functions in the emerging South African market.

Six fundamental factors were included in two diverse multifactor smart beta portfolios to determine the portfolio implications. The selected fundamental factors were value (Fama & French, 1993), profitability (Fama & French (2014), momentum (Jegadeesh & Titman, 1993), liquidity (Pástor & Stambaugh, 2003), investment (Fama & French, 2014) and high yield (Graham & Dodd, 1951). This study aimed to establish how these individual fundamental factors react to various portfolio rebalancing decisions and the inherent classification persistence of stocks.

If the study succeeds in providing more transparency of smart beta portfolios, it will be a useful tool for market participants who want to invest by using a smart beta strategy. Furthermore, fund managers who are attempting to successfully manage a smart beta fund may specifically find value in the insights provided by this study.

6.2 SUMMARY OF EMPIRICAL RESULTS

In order to provide a deeper understanding of smart beta funds, the portfolio rebalancing implications were measured for net returns and secondly, for portfolio churn. Research Objectives I and II suggested the adoption of a quarterly rebalancing strategy as it consistently delivered outperformance even when confronted with additional portfolio churn. The inherent ability of the selected fundamental factors to correctly identify outperforming stocks justifies the use of quarterly rebalancing. Acting upon the changed signals generated returns to such an extent that the increased trading costs did not erode the net returns. The quarterly rebalanced multifactor portfolios, the fundamental factor performance history weighted fund (FFPHW) and the equally weighted multifactor fund (EWMF), outperformed the SWIX and ALSI benchmarks over the ten-year period in question, yielding a market-adjusted annualised return of 2.9 per cent and 6.2 per cent respectively. The value of investing in a smart beta strategy, however, only holds for a winner (long-only) portfolio strategy. The loser (short) portfolio strategy does not generate outperformance.

In an attempt to further investigate the portfolio and to understand the fundamental factors that drive multifactor portfolio returns, research Objective III was addressed. A regression analysis using the LASSO revealed that momentum and profitability are the primary drivers of return. The high yield and value fundamental factors also notably contributed to the outperformance of the multifactor portfolios. The individual fundamental factor's ability to drive returns was significantly different under different rebalancing frequencies. Although they are meaningful drivers of return under most rebalancing frequencies, momentum and profitability contributed most under more frequent rebalancing strategies. High yield and value performed significantly better under a less frequent rebalancing strategy.

Portfolio churn and its relationship with net returns and with classification persistence were studied under research Objective IV. More frequent rebalancing strategies were found to subject the resultant portfolio to additional portfolio churn. It was expected that an inverse relationship between portfolio churn and net returns would exist. Increased portfolio churn necessarily increases the trading costs payable, which in turn erodes net returns. However, contrary to the expectations, a significant negative correlation across all portfolios was not found. Only the FFPHW multifactor portfolio and, to a lesser extent, the high yield single-factor portfolio indicated a strong negative correlation between portfolio churn and net returns. A marginal benefit of return was therefore observed in the portfolio rebalancing decision. There is more value to be unlocked in trading more often at the expense of incurring additional trading costs. As a result, a more frequent rebalancing strategy is preferred.

The failure of the FFPHW portfolio to display this marginal benefit of return brings the portfolio's classification as a true smart beta fund (as defined by Arnott, 2016) into question. Arnott (2016) argues that a fund cannot be classified as a true smart beta fund without breaking the link with price that is inherent to a market capitalisation weighted strategy. As the FFPHW portfolio selects stocks based on the past return performance of fundamental factors, it incorporates price into the selection process. The inclusion of price therefore erodes the marginal benefit of return that the other portfolios enjoy because of the lack of an inverse relationship between portfolio churn and net returns. Future research could further investigate this trade-off between incorporating price history into smart beta portfolio construction and benefiting from the investment value inherent to the fundamental factors.

The classification persistence of stocks, which addressed the stability of smart beta portfolios, was determined under the remaining research Objectives, namely V, VI and VII. In other words, these research objectives were to determine whether a stock would remain classified as a winner (buy), neutral, or a loser (sell) signal for the upcoming month. A look-back period of four, five and six months respectively was implemented to determine the classification persistence. The classification persistence of these stocks was significantly high, and remained so for all the look-back periods investigated. Economic conditions are therefore considered to have a minor influence on the stability of these stock classifications. However, as stocks must have already persisted for at least four months to be considered in the classification persistence analysis, this finding only suggests that stable stocks remain stable. Unstable stocks, i.e. stocks that persisted for less than four months, were not considered.

The classification persistence of the winner portfolio proved to be weaker than that of the loser portfolio. Thus, the winner portfolio inherently requires more trading than the loser portfolio and is updated more frequently. The classification persistence of stocks also proved to be insensitive to both sector categories and economic conditions.

6.3 CONCLUSIONS

The empirical results discussed in the preceding section provided an introduction to the study's overall conclusions. These conclusions will be discussed next.

6.3.1 The portfolio implications of including individual fundamental factors in the South African context

The South African emerging market presents unique challenges and opportunities in the investment arena. The investment value of fundamental factors, in other words their ability to consistently identify outperforming stocks, is critical to the success of the portfolio. High investment value offers the opportunity to justify frequent rebalancing if the fundamental factors manage to act as adequate drivers of return. Portfolio after-cost returns were used as a measure to evaluate the portfolio construction implications. The study therefore evaluated the portfolio implications of including individual fundamental factors on the multifactor portfolios, rather than conducting a pure performance analysis of fundamental factors. The significance of this investment value that is derived from each fundamental factor was then exhibited by their ability to act as a driver of return in the multifactor portfolios. The following insights into the individual fundamental factors were obtained in this study.

6.3.1.1 Momentum

Contrary to what Van Heerden (2014) reported, this study found that significant investment value can be derived from momentum as the winner portfolio significantly outperformed the loser portfolio over time in the South African context. The investment value, however, diminished as rebalancing frequencies decreased. Momentum is therefore considered to be a preferred short-term fundamental factor. This fundamental factor generated superior outperformance under a quarterly rebalancing strategy as the profits due to the underlying stock price movements were locked in before the stock mean-reverted. A less frequent rebalancing strategy fails to lock in profits before the stock prices mean-reverts.

A diversification benefit from including the momentum fundamental factor in the multifactor portfolio was observed as momentum net returns were negatively correlation with other fundamental factor net returns, except with profitability.

Momentum net returns were specifically negatively correlated with the net returns of the high yield, investment and value fundamental factors. Therefore, by including momentum and profitability in the multifactor portfolio the downside risk of the portfolio is decreased.

The momentum fundamental factor also demonstrated the weakest classification persistence and high portfolio churn compared to the five other single-factor portfolios. Including the momentum fundamental factor under a less frequent rebalancing strategy was inefficient as returns were not realised, while portfolio churn was still increased. However, under a quarterly rebalancing strategy, momentum acts as the primary driver of net returns. The benefit due to including momentum under a quarterly rebalancing strategy therefore outweighs the increased costs because of the increased portfolio churn.

6.3.1.2 Profitability

Profitability as measured by ROE specifically proved to be of exceptional value in a smart beta multifactor portfolio in the South African context. Profitability also proved to be the most consist fundamental factor as it added value to the multifactor portfolios under most portfolio construction scenarios. Not only does profitability offer invaluable investment value and exceptionally strong classification persistence across varying economic market conditions, it had a moderately negative or no correlation with other single-factor portfolio net returns. The profitability fundamental factor therefore acts as a unique driver of multifactor portfolio return. This negative correlation in turn, offers diversification benefits which increases multifactor portfolio risk-adjusted returns.

Oddly, profitability’s portfolio churn and after-cost returns were inversely correlated. Rebalancing more often therefore increased the net returns generated by the profitability fundamental factor. A quarterly rebalancing strategy takes advantage of this relationship as it trades more often.

6.3.1.3 High yield

At times high yield managed to act as the biggest driver of return, but failed to do so consistently. The value of including high yield in a multifactor portfolio, however, increases as the rebalancing frequency decreases. Yet, this relationship between investment value and rebalancing frequency is not mirrored by the primary drivers of return, namely profitability and momentum, and therefore will not be a deciding factor in selecting a rebalancing strategy.

The high yield fundamental factor is more stable than most other fundamental factors with regard to classification persistence. Strong classification persistence and the lowest portfolio churn (33%) of all single-factor portfolios were observed. An inverse relationship, however, exists between weak classification persistence and net returns for the high yield fundamental factor. Increased trading therefore diminishes after-cost returns. As a result, a less frequent rebalancing strategy is preferred for the high yield fundamental factor.

The investment value derived from the high yield fundamental factor diminished completely in the last three years of the research period. The loser high yield portfolio significantly outperformed the winner high yield portfolio across all rebalancing strategies. There is risk involved in including the high yield strategy in the multifactor portfolio as it fails to consistently identify the potential outperforming stocks in the South African context.

6.3.1.4 Liquidity

No noticeable difference between the winner and loser liquidity portfolios was observed. Therefore, little investment value is derived from including the liquidity portfolio in a multifactor portfolio. This assumption is supported by the fact that liquidity was the only single-factor winner portfolio that underperformed the benchmark on a cumulative scale over the entire ten-year research period.

In addition to the weak investment value of liquidity, liquidity subjects the multifactor portfolio to more churn than other fundamental factors. Furthermore, at 44 per cent, liquidity had the highest average annual portfolio churn of all portfolios, thereby further decreasing the after-cost performance. The inclusion of the liquidity fundamental factor seems to have no significant implication on the multifactor portfolios other than subjecting it to large portfolio churn and minimal benefit as a trade-off.

6.3.1.5 Investment

Following Fama and French's (2014) investment approach, the investment fundamental factor specifically identified stocks with little change in total assets (low investment) as a winner stock and the stocks with the largest changes in total assets (high investment) as a loser stock. The high investment stocks, however, outperformed the low investment stocks in the South African environment. This outperformance may be due to South African firms making large international investments during the ten-year research period. The Rand weakened significantly during this same period. Therefore, returns of high investment stocks may be driven by the Rand/Dollar effect rather than the inherent increase in value of the specific stocks. Further research into the investment fundamental factor in the South African context is necessary to determine whether this reversed investment value, which contradicts the findings of Fama and French (2014), is a consistent or temporary phenomenon.

6.3.1.6 Value

The value fundamental factor portfolio failed to consistently identify the outperforming stocks while subjecting the portfolio to above average, annual average portfolio churn of 40 per cent. A semi-annual rebalancing strategy proved to be profitable for the value fundamental factor, especially in times of financial market upset. The value fundamental factor, as measured by earnings yield, attempts to identify stocks that will outperform due to their inherent qualities. In times of financial turmoil, these stocks therefore manage to perform better than growth stocks as they have underlying qualities that drive their returns other than market sentiment. The value fundamental factor therefore underperforms when the market is performing significantly well as they are affected less by market noise.

6.3.2 Classification persistence implications

Except for momentum, all single-factor portfolios managed to maintain high classification persistence over time. Both multifactor portfolios managed to maintain moderately high classification persistence averaging 0.73 and 0.66 respectively for the winner portfolio. The loser portfolio consistently delivered stronger classification persistence than the winner portfolio.

Classification persistence, however, proved to be a weak indicator of net returns. It was expected that weak classification persistence, in other words a low probability of signals remaining unchanged for the following month, would lead to increased churn and therefore decreased net returns. However, only high yield as a single-factor portfolio and the EWMF multifactor portfolio displayed this expectedly strong negative correlation between classification persistence and portfolio churn. The EWMF portfolio displayed a moderately negative correlation again between portfolio churn and net returns. Thus, the only portfolio for which classification persistence strength is an indicator of net returns is the EWMF portfolio. The other portfolios indicate no definable relationship between classification persistence strength and net returns. This again can be attributed to the weak smart beta trade-off as the benefit of acting on changing smart beta signals outweigh the loss due to the increased trading costs.

6.3.3 Optimal rebalancing frequency and the smart beta trade-off

Research Objectives I, II, III and IV contributed to the aim of identifying an optimal rebalancing frequency. A holistic view was taken of the impact of the selected rebalancing frequency on i) net returns, ii) market-adjusted returns and iii) portfolio churn, to identify a quarterly rebalancing frequency as the optimal strategy. A discussion of the results leading to this conclusion follows.

Several factors supported the decision to suggest a quarterly rebalancing strategy as the rebalancing strategy which offers the best performance all things considered. First, the strength of the smart beta trade-off essentially determined which rebalancing strategy is optimal. Research Objective IV brought this trade-off to light. The trade-off states that more trading due to a more frequent rebalancing strategy will lead to increased trading costs and therefore decreased net returns unless the investment value derived from the fundamental factors is of such an extent that net returns are not eroded by the increased costs. The trade-off proved to be weak as there is more benefit in acting on the changing fundamental factor signals at the expense of incurring the additional trading costs. This weak trade-off is indicated by the lack of a negative correlation between portfolio churn and net returns. The increased return due to rebalancing more frequently therefore does not decrease net returns. A more frequent rebalancing frequency is therefore desirable. A monthly rebalancing strategy, however, proved to be too short-lived for stock outperformance to be consistently realised. A quarterly rebalancing strategy was identified as the optimal strategy as it consistently offered outperformance.

Second, individual fundamental factors delivered varying results for different rebalancing strategies. For instance, the investment value derived from momentum decreased significantly as rebalancing frequencies increased. The correlation of net returns between portfolios also varied significantly under different rebalancing strategies. By addressing research Objectives I and II it was clear that a quarterly rebalancing strategy offered consistent outperformance compared to other rebalancing strategies. This outperformance is driven by profitability and momentum which loses investment value and the resultant ability to drive returns under different rebalancing strategies as indicated by research Objective III.

Finally, considering that portfolio churn does not have a significantly negative correlation with classification persistence, trades cannot merely be attributed to large changes in the underlying stocks. Strong classification persistence suggests that the majority of portfolio churn is merely due to rebalancing the portfolio to the desired weights rather than changing the stocks held in the portfolio. As the portfolio rebalances quarterly, it is capitalising on the profit realised during the three months, while also assuring that the 30 stocks expected to offer the best outperformance are held by the portfolio. This process proves to deliver the best results under a quarterly rebalancing strategy.

6.3.4 Multifactor fund evaluation

Two diverse portfolio construction methodologies were implemented. Both only identified the 30 best-performing stocks as a winner (buy), however, the method that was applied to identify the top 30 stocks differs. The EWMF portfolio allocated equal weights to each signal when building a cumulative signal scorecard and selected the top 30 stocks from there. The FFPHW portfolio in turn assigned additional weight to the fundamental factor signals that outperformed in the previous twelve months. The top 30 stock selection of the FFPHW portfolio is therefore skewed to favour previously outperforming single-factor portfolio signals. Once the top 30 stocks were identified, however, both portfolios assigned equal weights of 3.33 per cent to each stock.

Both multifactor strategies managed to outperform both the SWIX and ALSI benchmarks. However, the EWMF strategy offers greater outperformance and is less volatile than the FFPHW portfolio. Fundamental factors therefore seem to outperform when combined, rather than when simply selecting (overweighting) a few ‘superior’ fundamental factors. A multifactor portfolio fundamental factor selection is therefore expected to benefit from including a few fundamental factors, rather than trying to limit the number of fundamental factors considered.

6.4 RECOMMENDATIONS

The value of this study is measured by its ability to be successfully implemented by investment professionals in their attempts to become more successful in their profession. The value to investors and smart beta professionals in particular is therefore called into question.

6.4.1 Portfolio construction implications for smart beta fund managers

This study supports the inclusion of the profitability and momentum fundamental factors in a smart beta portfolio. High yield and value also offer some benefits, while investment and liquidity should be excluded from the portfolio. The EWMF portfolio, an equally weighted, long-only, multifactor strategy managed to significantly outperform the selected benchmarks. It is therefore suggested as a profitable approach to construct a smart beta multifactor portfolio. A quarterly rebalancing strategy should be implemented to benefit from the marginal benefit of the return observed.

There is investment value to be derived from smart beta fundamental factors in the South African environment. The outperforming stocks have consistently been identified as a winner (buy) signal and therefore fund outperformance was observed. Additionally, this study determined that increased portfolio churn and therefore increased trading does not erode net returns as the investment value driving the trading signals are accurate. Smart beta fund managers should therefore trust the signals derived from the fundamental factors and act on these signals.

6.4.2 Index-tracking using a smart beta investment philosophy

The winner portfolio consistently identified the desirable stocks which generated outperformance. The loser portfolio in turn underperformed significantly. Therefore, it can be assumed that the loser portfolio correctly identified the undesirable stocks. The smart beta investing method can therefore be implemented by a passive index-tracking fund manager to correctly identify which stocks should be over- or underweighted. The stocks included in the index being tracked are therefore the smart beta investment universe. Applying the smart beta fundamental factor requirements will therefore identify the winner and loser stocks. The loser stocks can then be underweighted while the winner stocks are overweighted. This practice is generally referred to as 'factor-tilting'. The index-tracking portfolio should therefore manage to passively outperform its index. However, Arnott (2016) argues that this is an ineffective strategy of tracking an index as it typically fails to benefit from the inherent smart beta strategy investment value. Further research should therefore be conducted to evaluate the success of factor-tilting as recommended here in the South African environment.

6.5 LIMITATIONS AND FUTURE RESEARCH

All research studies can inevitably be improved. This particular study only used six fundamental factors to test what happens in a smart beta portfolio. Future studies can be conducted to test whether the findings in this study hold for different combinations of fundamental factors. In addition, other multifactor portfolio construction methodologies can be tested and compared to the findings for the EWMF and FFPHW portfolio. More specifically, the trade-off between incorporating price into stock selection in a smart beta fund, such as the FFPHW portfolio, and benefitting from the smart beta marginal benefit of return should be investigated.

Due to data limitations, the study could only investigate a ten-year research period. Further studies can be conducted for different periods of time. The results are also specific to the South African environment. However, it is expected that similar results would be found for other emerging markets.

Further research into the reversed investment fundamental factor in the South African context can be of value. Contrary to what Fama and French (2014) suggest, the high investment stocks outperformed the low investment stocks. This phenomenon was hypothesised to be a result of the Rand/Dollar effect, meaning that many South African firms consciously increased their international exposure during the research period while the Rand weakened significantly over the same period.

6.6 RECONCILIATION OF RESEARCH OBJECTIVES

Various research objectives were addressed in the study. The classification persistence of stocks in particular was determined for each portfolio as well as across sectors and the winner and loser stocks were compared. It was therefore possible to determine the relationship between classification persistence, portfolio churn and net returns. This relationship suggested that a weak smart beta trade-off exists between trading costs and the benefit derived from acting on the relevant buy, neutral or sell signals. Furthermore, the portfolio rebalancing implications on i) portfolio churn, ii) after-cost performance and iii) the ability of the portfolio to outperform the relevant benchmark, were measured. A quarterly rebalancing strategy could therefore be suggested as the optimal strategy to ensure outperformance. Lastly, the drivers of return were also identified. All the information collected could be reconciliated to provide a holistic recommendation of how to optimally approach a smart beta portfolio construction in the South African context.

6.7 CONCLUDING REMARKS

The aim of this study was to identify the portfolio construction implications of using various smart beta fundamentals. The effect of different rebalancing strategies and classification persistence of stocks on net returns and on portfolio churn was investigated. The study attempted first to identify the relationships that arise in a smart beta portfolio due to various portfolio construction methodologies and second, the study used performance analysis, under each different portfolio construction methodology, to determine its validity in the South African smart beta context.

As alluded to earlier, South Africa was late to introduce smart beta funds into the market compared to the global developments in smart beta. The few smart beta funds that have been introduced were mostly launched after 2010. The South African smart beta environment was found to be noticeably more profitable before 2012. These funds were therefore constructed based on back-testing which proved to be exceptionally profitable, but had difficulty to outperform the market once in operation. This study can assist in the implementation of smart beta as a viable fund management technique over the long term, and also explains some of the relationships among variables in a smart beta fund which leads to under- or outperformance.

Smart beta has value in the South African context if managed correctly. The profitability and momentum fundamental factors have specifically proved to offer significant investment value when combined with a quarterly rebalancing strategy. The investment value derived from fundamental factors illustrates their ability to correctly identify outperforming stocks. Trading on these fundamental factor signals, even at the expense of increased trading costs, returned after-cost outperformance. Smart beta is therefore accepted to be a profitable strategy in the South African environment when investing over a longer time horizon.

Only the FFPHW portfolio indicated a significant inverse relationship between portfolio churn and net returns. This lack of a consistent inverse relationship is considered further evidence of the value of a true smart beta fund. The benefit of trading according to the fundamental factor signals therefore outweighs the inherent trading costs that are associated with the increased portfolio churn. This result supports the finding that there is investment value to be derived from some of the six selected fundamental factors used in this study. The investment and liquidity fundamental factors are considered of little value in the South African context while profitability and momentum are considered of significant value.

All single-factor portfolios except for momentum managed to maintain strong classification persistence. Momentum as well as both multifactor funds maintained lower classification persistence, although still moderately high. However, no significant relationship could be found between classification persistence and net returns. Classification persistence is therefore considered a weak indicator of future net returns. The classification persistence of stocks is not significantly sensitive to sector categories of stocks or economic cycles.

The FFPHW portfolio is a new contribution to the existing body of knowledge on smart beta. The portfolio construction methodology, to the knowledge of the researcher, has not been described and assessed in previous literature. The FFPHW portfolio was constructed to test the methodology of weighting fundamental factors according to their past performance. The portfolio managed to deliver 2.9 per cent SWIX and 3.8 per cent ALSI market-adjusted performance. The EWMF portfolio, which instead equal weights each fundamental factor, however, outperformed the FFPHW portfolio by 3.3 per cent (annualised return). There is value in the FFPHW portfolio methodology as it outperformed both benchmarks. However, an equal-weighting strategy among multiple factors offers more value than selecting a few superior fundamental factors and overweighting the exposures in the portfolio to these select few.

Smart beta is therefore considered a profitable investment strategy in the South African context. This study provided insights into the relationships inherent to a smart beta portfolio and attempted to develop guidelines for optimal portfolio management. Investment professionals are thus advised to consider the findings of this study when constructing and managing a smart beta portfolio in South Africa.

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ANNEXURE A: SUMMARY OF FACTORS IDENTIFIED IN PAST LITERATURE

Unless stated otherwise, the relationship is of a positive nature with earnings or stock performance.

	FACTOR	RELATIONSHIP*	AUTHOR(S)
TECHNICAL	Relative strength	Weighted ≥70	Reinganum (1988)
		≥ 70 based on: Top 2/3 companies ranked by annual earnings and sales growth, profit margins (pre- and post-tax), ROE, product quality.	O'Neil (2002)
		Higher 2-year return until 1 year ago→ lower expected 3-month return	Glickman et al. (2001)
	Change in relative strength	Positive from previous quarter	Reinganum (1988)
	Daily volatility	Higher over previous quarter	Glickman et al. (2001)
	Momentum	Lower past 1-year return → lower expected 3-month return	
	Age	Younger companies	
	Market capitalisation	Smaller	
		Smaller to be avoided	O'Neil (2002)
	Stock price	Within 15% of 2-year high	Reinganum (1988)
		Within 15% of year's high Buy more securities if price > 2-3% above purchase price Stop buying after increase of 5% Sell if price < 7% below purchase price	O'Neil (2002)
	Daily trading volume	Increase by at least 50% above average	

		Higher prior 6-month average	Glickman et al. (2001)
	# stocks outstanding	< 25 million	O'Neil (2002)
		< 25 million	Reinganum (1988)
	Standard deviation		Tunstall, Stein and Carris (2004)
Fundamental	P/B	< 1	Reinganum (1988)
	Diluted earnings to price	Inconclusive	Glickman et al. (2001)
	I/B/E/S Long term growth	Larger long term means	
	Annual earnings growth	Top ranked (industry)	O'Neil (2002)
	Annual sales growth	Top ranked (industry)	
	Post-tax profit margin	Top ranked (industry)	
	Pre-tax profit margin	Top ranked (industry)	
	Quarterly earnings	Acceleration	Reinganum (1988)
	Quarterly sales	Acceleration	
	5-year quarterly earnings growth	Positive	
	Accruals / Total Assets	Fewer income-increasing accruals	Glickman et al. (2001)
	Receivables	Lower	
	Operating cash flow	Higher, Do not experience decrease over past year	
	Quarterly EPS	18-20% higher; accelerated growth	
	Annual EPS	Annual growth of 25% over past 3 years	
	Annual pre-tax profit margin	Increasing	O'Neil (2002)
	Expected earnings	Consensus reasonable increase	
	ROE	≥17% ;Top ranked (industry)	
	% Δ in current ratio		Ou and Penman (1989)
	% Δ in quick ratio		
	% Δ in inventory turnover		
	Inventory/Total Assets		
	% Δ in Inventory/Total Assets		
	% Δ in inventory		
	% Δ in sales		

	% ∆ in depreciation		
	·∆ DPS		
	% ∆ in (depreciation/plant assets)		
	Return on opening equity		
	% ∆ in return on opening equity		
	% ∆ in capital expenditure / total assets		
	% ∆ in capital expenditure / total assets, lagged 1 year		
	Debt-equity		
	% ∆ in Debt/Equity		
	% ∆ in Sales/Total assets		
	Return on total assets		
	Return on closing equity		
	Gross margin ratio		
	% ∆ in pre-tax income / sales		
	Sales/Total cash		
	% ∆ in Total assets		
	Cash flow / Debt		
	Working capital / Total assets		
	Operating income/Total assets		
	Repayment of LT debt as % of total LT debt		
	Cash dividend / cash flow		
	∆ Inventory – ∆ Sales		Lev and Thiagarajan (1993)
	∆ Accounts receivable – ∆ Sales		
	∆ Industry capital expenditure – ∆ Firm capital expenditure		
	·∆ Sales – ∆ Gross margin		
	∆ Selling and administrative expenses – ∆ Sales		
	Effective tax rate		
	∆ Sales – ∆ Order backlog		
	Labour Force		
	Audit qualification		
	LIFO vs. FIFO earnings		
	EBITDA		Liu, Nissim and Thomas (2002)
	Dividend yield		O'Shaughnessy (2005)
	Price/Cash flow		
	Sales/Price		Mukherji and Raines (1996)

	Payout ratio		Tunstall, Stein and Carris (2004)
Macro-economic	Inflation		Lev and Thiagarajan (1993)
	GNP		
	Business inventories		
	Resources index		Van Rensburg (2002)
	Financial industrial index		
Other	Stock buybacks	Yes	O'Neil (2002)
	Management ownership	Yes	
	Number of institutional owners	Major increase between quarters	Reinganum (1988)
		≥ 25 ;Must have increased during past few quarters	O'Neil (2002)
	% stocks owned by institutions	5% - 35%	
		Major increase between quarters	Reinganum (1988)
	Product quality	Top ranked (industry)	O'Neil (2002)

Adapted from Van Heerden (2014)

ANNEXURE B: SMART BETA INVESTING AS EXPLAINED BY BLACKROCK

An insight into smart beta investing by leading global asset manager BlackRock.

Systematic Factors	What It is	Commonly Captured by
Value	➢ Captures excess returns to stocks that have low prices relative to their fundamental value	➢ Book to price, earnings to price, book value, sales, earnings, cash earnings, net profit, dividends, cash flow
Low Size (Small Cap)	➢ Captures excess returns of smaller firms (by market capitalization) relative to their larger counterparts	➢ Market capitalization (full or free float)
Momentum	➢ Reflects excess returns to stocks with stronger past performance	➢ Relative returns (3-mth, 6-mth, 12-mth, sometimes with last 1 mth excluded), historical alpha
Low Volatility	➢ Captures excess returns to stocks with lower than average volatility, beta, and/or idiosyncratic risk	➢ Standard deviation (1-yr, 2-yrs, 3-yrs), Downside standard deviation, standard deviation of idiosyncratic returns, Beta
Dividend Yield	➢ Captures excess returns to stocks that have higher-than-average dividend yields	➢ Dividend yield
Quality	➢ Captures excess returns to stocks that are characterized by low debt, stable earnings growth, and other "quality" metrics	➢ ROE, earnings stability, dividend growth stability, strength of balance sheet, financial leverage, accounting policies, strength of management, accruals, cash flows

Systematic Factors	Systematic Risk-based Theories[17]	Systematic Errors-based Theories[18]
Value	➢ Higher systematic (business cycle) risk	➢ Errors-in-expectations ➢ Loss aversion ➢ Investment-flows-based theory
Low Size (Small Cap)	➢ Higher systematic (business cycle) risk ➢ Proxy for other types of systematic risk	➢ Errors-in-expectations
Momentum	➢ Higher systematic (business cycle) risk ➢ Higher systematic tail risk	➢ Underreaction and overreaction ➢ Investment-flows-based theory
Low Volatility	➢ N/A	➢ Lottery effect ➢ Overconfidence effect ➢ Leverage aversion
Dividend Yield	➢ Higher systematic (business cycle) risk	➢ Errors-in-expectations
Quality	➢ N/A	➢ Errors-in-expectations[19]

	Current Framework	Possible New Framework
Strategy	➢ Diversification across managers in multiple alpha mandates ➢ Asset owner manages strategy through asset allocation and manager selection	➢ Diversification across strategies in multiple factor index mandates ➢ Asset owner manages strategy through factor allocation
Roles and Tools	➢ Alpha is defined broadly: bottom-up skill, top-down sources and timing ➢ Risk control is principally through asset allocation and manager diversification	➢ Alpha is defined more narrowly excluding factors ➢ Risk control focuses on managing exposure to risk factors
Economics	➢ Active mandates dominate the portfolio's costs ➢ Large line-up of external managers with small internal asset owner staff	➢ Active mandates co-exist with factor mandates producing lower costs ➢ Larger internal staff managing more assets with fewer external managers

Source: BlackRock, 2017

ANNEXURE C: RAFI FUNDAMENTAL INDEX PERFORMANCE AND RISK STATISTICS

Sources: CRSP/Compustat and Worldscope/Datastream	RAFI Fundamental Index				
Description	The RAFI Fundamental Index simulation is based on **RAFI US Fundamental Index** methodology to select and weight companies according to four fundamental measures of company size: book value, cash flow, dividends+buybacks, and adjusted sales. Four tranches are each rebalanced annually for a quarterly staggered rebalance. Learn More				
EXPECTED RETURNS (ANN.)	NET OF TRADING COST		GROSS OF TRADING COST		
Expected Excess Return Over Market Benchmark	1.66%		1.68%		
Tracking Error	3.7%				
Information Ratio (Gross)	0.45				
Confidence Interval: Expected Return (Gross)	95TH	75TH	50TH	25TH	5TH
	-1.2%	0.5%	1.68%	2.8%	4.5%
Real Return	1.83%		1.85%		
Confidence Interval: Real Return (Gross)	95TH	75TH	50TH	25TH	5TH
	-3.3%	-0.3%	1.85%	4.0%	7.0%
Nominal Return	4.05%		4.07%		
Confidence Interval: Nominal Return (Gross)	95TH	75TH	50TH	25TH	5TH
	-1.1%	1.9%	4.07%	6.2%	9.3%
Volatility	14.1%				
Sharpe Ratio	0.17				
Market Beta	1.00				

VALUATIONS (STRATEGY VS. MARKET)	
Current (Aggregate)	0.70
Median (Aggregate)	0.71
Current (P/B)	0.69
Median (P/B)	0.74

	RAFI Fundamental Index	
HISTORICAL (1968 -) (ANN.)	NET OF TRADING COST	GROSS OF TRADING COST
Excess Return Over Market Benchmark	1.49%	1.51%
Tracking Error	4.2%	
Information Ratio (Gross)	0.39	
Real Return	7.21%	7.23%
Nominal Return	11.59%	11.61%
Structural Alpha	1.58%	
Revaluation Alpha	-0.07%	
Volatility	14.8%	
Sharpe Ratio	0.46	
Market Beta	0.93	

	RAFI Fundamental Index	
HISTORICAL (RECENT 5 YEARS) (ANN.)	NET OF TRADING COST	GROSS OF TRADING COST
Excess Return Over Market Benchmark	0.51%	0.53%
Tracking Error	2.4%	
Information Ratio (Gross)	0.25	
Real Return	12.36%	12.38%
Nominal Return	13.74%	13.76%
Volatility	10.6%	
Sharpe Ratio	1.29	
Market Beta	1.02	

	RAFI Fundamental Index
COSTS AND CAPACITY	
Estimated Trading Cost	0.02%
Capacity	$272B
Turnover	11.4%
Weighted Average Market Cap	$140B
Effective Number of Stocks	119

Source: Research Affiliates, 2017

ANNEXURE D: INVESTMENT FACTOR LOOK-BACK PERIOD

Based on the following statistical tests it was concluded that a twelve-month look-back strategy for the investment fundamental factor won't offer statistically significant different results than a twenty-four month look-back strategy. Using a single factor ANOVA test there was no statistically significant difference in the average return of twelve month look-back in comparison to the twenty-four month look-back. Single factor ANOVA was conducted with the following hypothesis at a 5% level of significance.

$$H_0: \mu_1 = \mu_2$$

$$H_A: \mu_1 \neq \mu_2$$

REBALANCING FREQUENCY	**P-value**
Monthly	0.902352
Quarterly	0.902352
Semi-annually	0.570212
Annually	0.417218

Thus, no p-value justified rejecting the null hypothesis (*p* > .05) and therefore it cannot be concluded that neither twelve month nor twenty-four month outperforms the other.

ANNEXURE E: LASSO REGRESSION R CODE

```
######Importing the data into R

data <- read.Table(file= "clipboard", header = T, sep="\t")
data

#scaling the x variables for lasso
x.var <- as.matrix(data[,2:7])
x <- scale(x.var)
y.var <-  as.matrix(data[,1])

#performing the Lasso
fit.lasso <- glmnet(x, y.var, family="gaussian", alpha=1)
plot(fit.lasso, xvar="lambda")

#####Correlation
library(corrplot)

M <- round(cor(data), digits = 2)
M
##  different color series
col1 <-
colorRampPalette(c("#7F0000","red","#FF7F00","yellow","white",
"cyan", "#007FFF", "blue","#00007F"))
## different color scale and methods to display corr-matrix
corrplot(M, method="color", col=col1(20), cl.length=21,
addCoef.col="white")
```

ANNEXURE F: SEMI-ANNUAL AND ANNUAL REBALANCING CORRELATION OF NET RETURNS

Individual fundamental factor and multifactor strategies net returns correlation is displayed here for a semi-annual and annual rebalancing strategy.

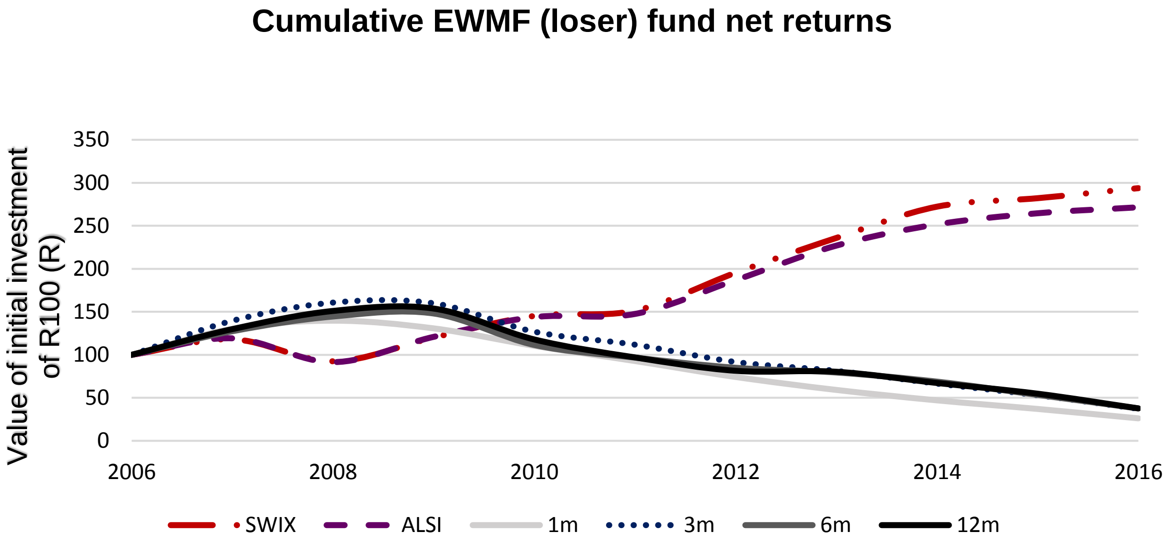
Net returns correlation heat map (semi-annual rebalancing)

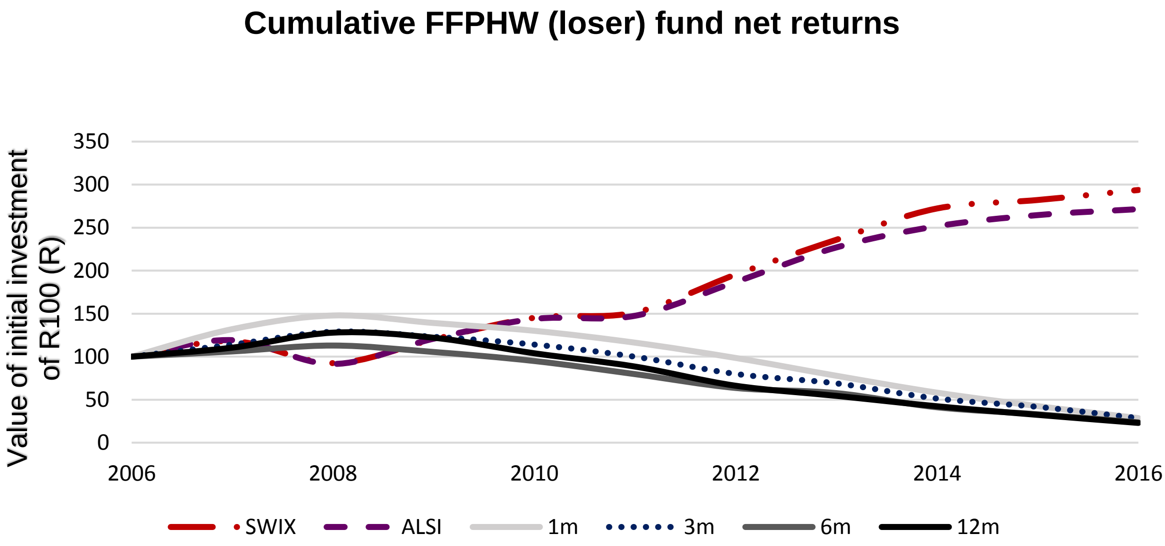
	FFPHW	EWMF	VALUE	PROF	MOM	LIQ	INV	HY
FFPHW	1.00							
EWMF	0.81	1.00						
VALUE	-0.21	-0.01	1.00					
PROF	-0.19	-0.20	0.64	1.00				
MOM	0.27	0.00	-0.21	0.12	1.00			
LIQ	0.15	-0.01	-0.50	-0.22	0.32	1.00		
INV	-0.13	0.01	0.05	-0.19	-0.16	-0.19	1.00	
HY	-0.13	0.22	0.38	-0.03	-0.33	-0.48	0.25	1.00

Net returns correlation heat map (annual rebalancing)

	FFPHW	EWMF	VALUE	PROF	MOM	LIQ	INV	HY
FFPHW	1.00							
EWMF	0.78	1.00						
VALUE	-0.01	0.26	1.00					
PROF	-0.38	-0.10	-0.11	1.00				
MOM	0.20	-0.06	-0.46	-0.03	1.00			
LIQ	0.14	-0.14	-0.51	-0.11	0.32	1.00		
INV	-0.10	0.02	0.22	-0.20	-0.04	-0.23	1.00	
HY	-0.06	0.19	0.62	0.03	-0.31	-0.55	0.22	1.00

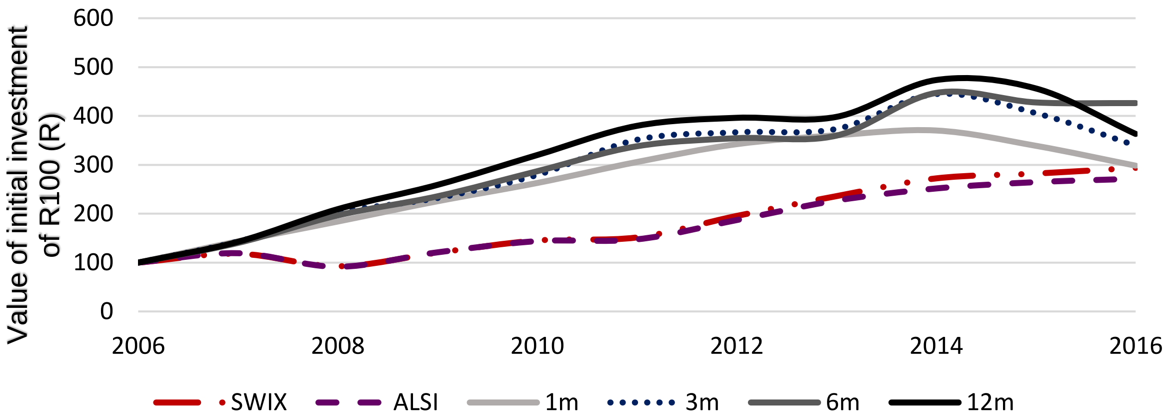
ANNEXURE G: LOSER PORTFOLIO FUND MARKET-ADJUSTED RETURNS



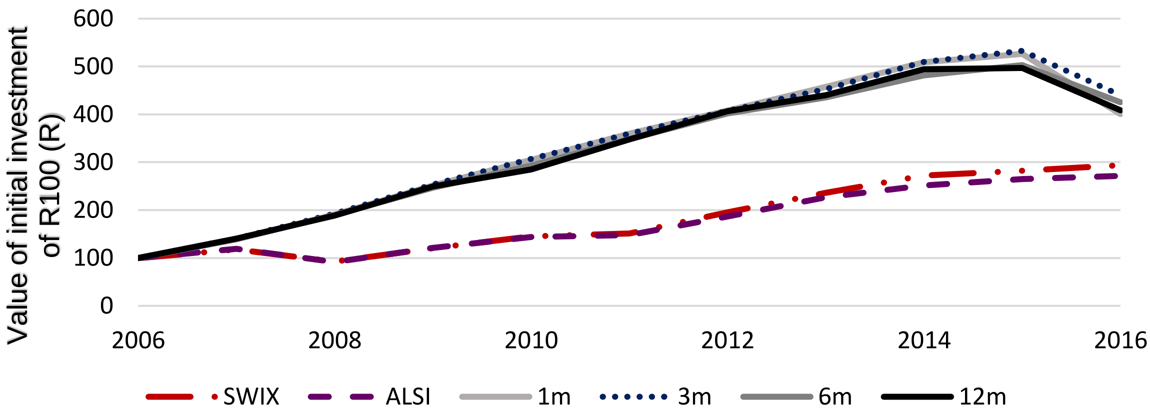


ANNEXURE H: ANNUAL NET RETURNS OF SINGLE-FACTOR FUNDS

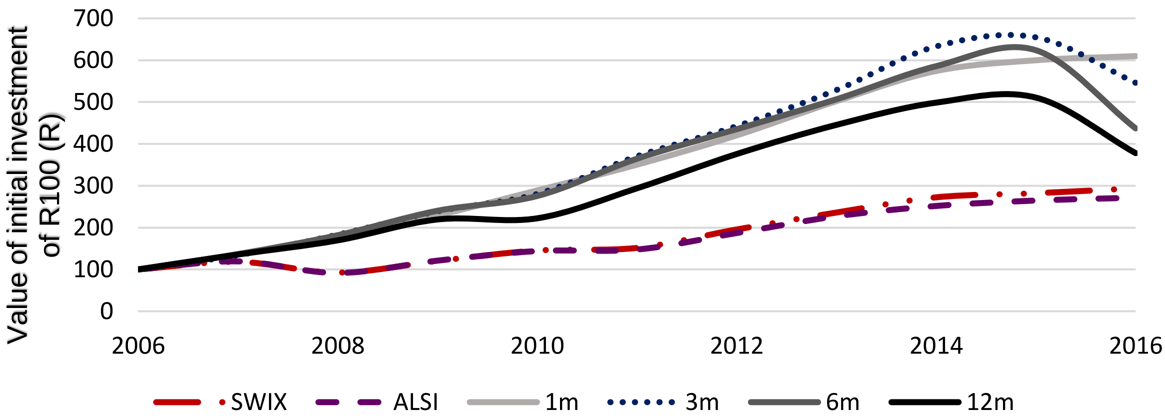
Cumulative value winner fund net returns



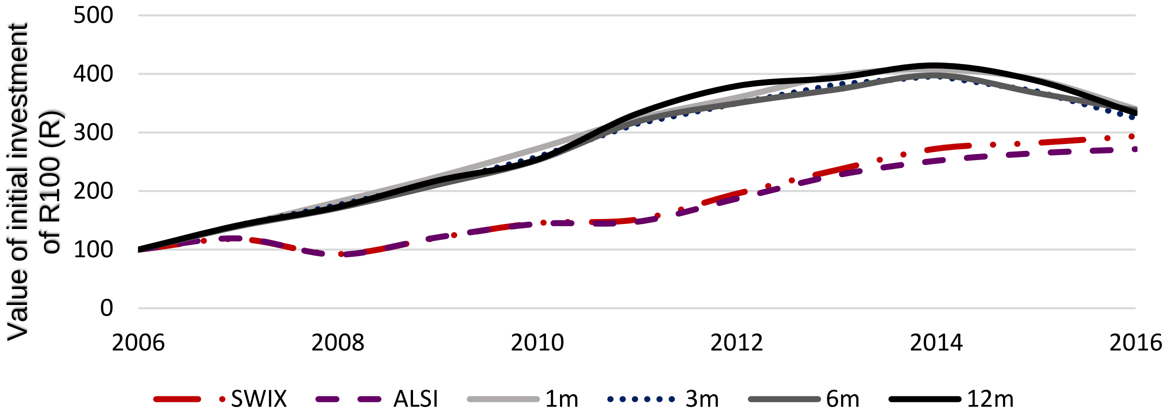
Cumulative profitability winner fund net returns



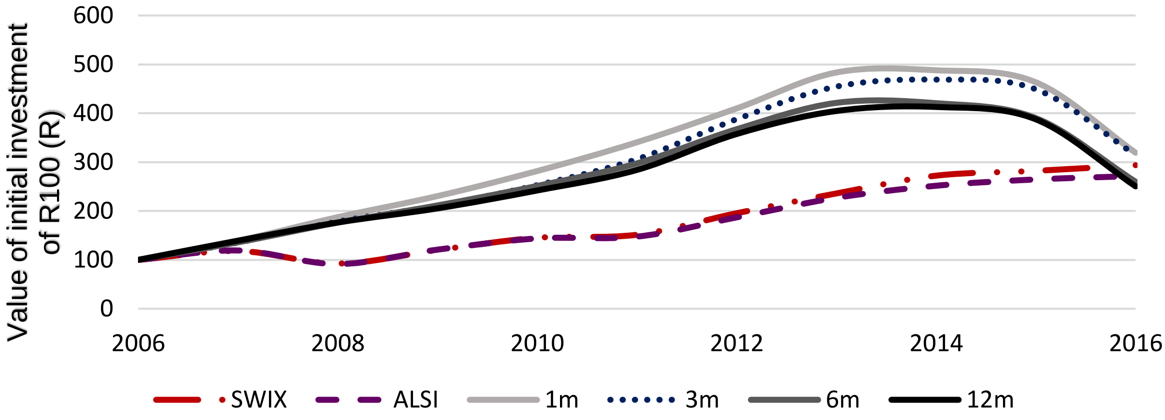
Cumulative momentum winner fund net returns



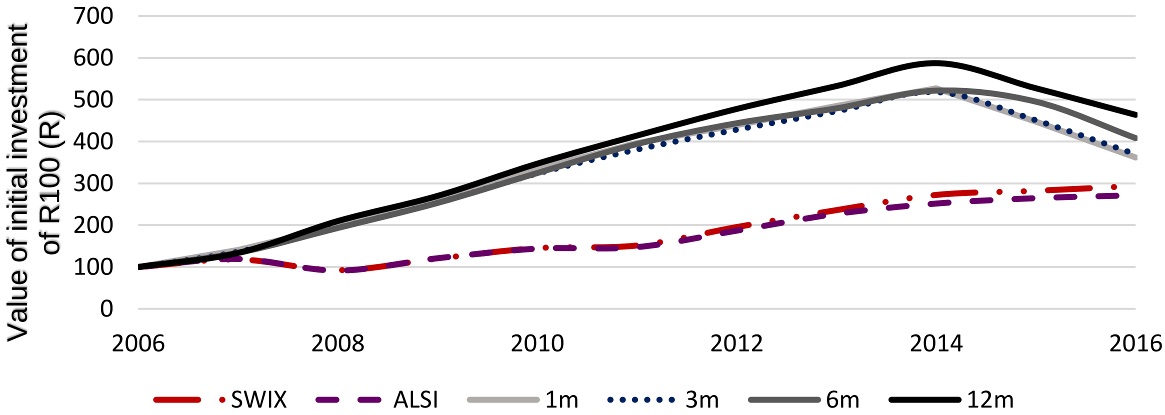
Cumulative investment winner fund net returns



Cumulative liquidity winner fund returns



Cumulative high yield winner fund net returns



ANNEXURE I: INFLUENCE OF REBALANCING FREQUENCY ON NET RETURNS

Hypothesis one states:

$$H_{10}: \mathcal{R}_1 = \mathcal{R}_3 = \mathcal{R}_6 = \mathcal{R}_{12}$$

$$H_{1A}: \mathcal{R}_1 \neq \mathcal{R}_3 \neq \mathcal{R}_6 \neq \mathcal{R}_{12}$$

The following *t*-tests addressed this hypothesis. The average difference between returns as well as the relevant t-statistic is displayed in the Table below. At a significance level of 5% all of the *t*-tests fail to indicate statistically significant outperformance. The study therefore fails to reject H_{10}.

Difference in returns of single-factor strategies for various rebalancing frequencies:

		1m	3m	6m
FFPHW	3m	1.60%		
		(-0.23)		
	6m	0.35%	-1.25%	
		(-0.05)	-0.15	
	12m	-1.36%	-2.96%	-1.71%
		-0.18	-0.35	-0.2
EWMF	3m	-0.30%		
		-0.05		
	6m	-4.96%	-4.66%	
		-0.85	-0.78	
	12m	-2.68%	-2.38%	2.28%
		-0.4	-0.35	(-0.37)
VALUE	3m	1.88%		
		-0.05		
	6m	3.92%	2.03%	
		(-0.53)	(-0.25)	
	12m	2.84%	0.96%	-1.08%
		(-0.34)	(-0.11)	-0.13
PROF	3m	0.79%		
		-0.05		
	6m	0.28%	-0.51%	
		(-0.04)	-0.07	
	12m	-0.02%	-0.81%	-0.30%
		0	-0.11	-0.04

MOM	3m	-0.68%		
		-0.05		
	6m	-2.61%	-1.93%	
		-0.37	-0.24	
	12m	-4.45%	-3.77%	-1.85%
		-0.64	-0.48	-0.21
INV	3m	-0.53%		
		-0.05		
	6m	-0.19%	0.34%	
		-0.03	(-0.05)	
	12m	-0.08%	0.45%	0.11%
		-0.01	(-0.06)	(-0.02)
LIQ	3m	-0.38%		
		-0.05		
	6m	-2.29%	-1.90%	
		-0.25	-0.21	
	12m	-2.59%	-2.20%	-0.30%
		-0.28	-0.24	-0.03
HY	3m	0.05%		
		-0.05		
	6m	1.01%	0.96%	
		(-0.11)	(-0.11)	
	12m	2.65%	2.60%	1.64%
		(-0.29)	(-0.29)	(-0.19)

Hypothesis two states:

$H_{20}: \mu_P = \mu_M$

$H_{2A}: \mu_P > \mu_M$

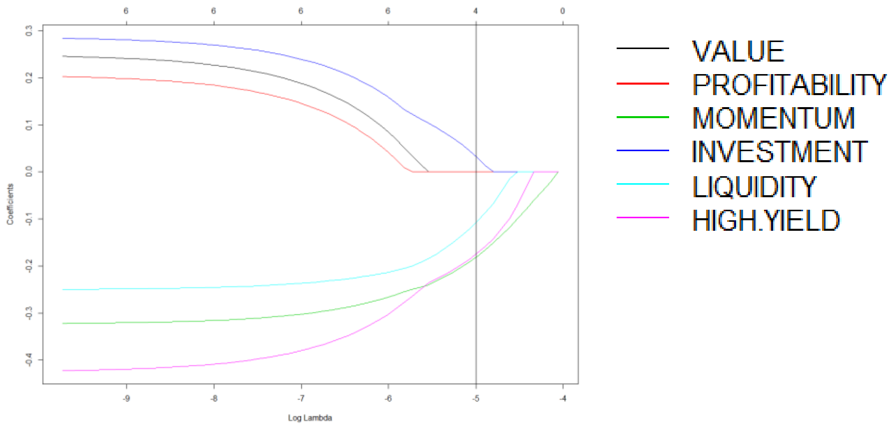
The following *t*-test results addressed this hypothesis. The average difference between returns as well as the relevant t-statistic is displayed in the Table below. At a significance level of 5% all of the *t*-tests fail to indicate statistically significant outperformance. The study therefore fails to reject H_{10}.

Difference in returns of multifactor strategies for various rebalancing frequencies:

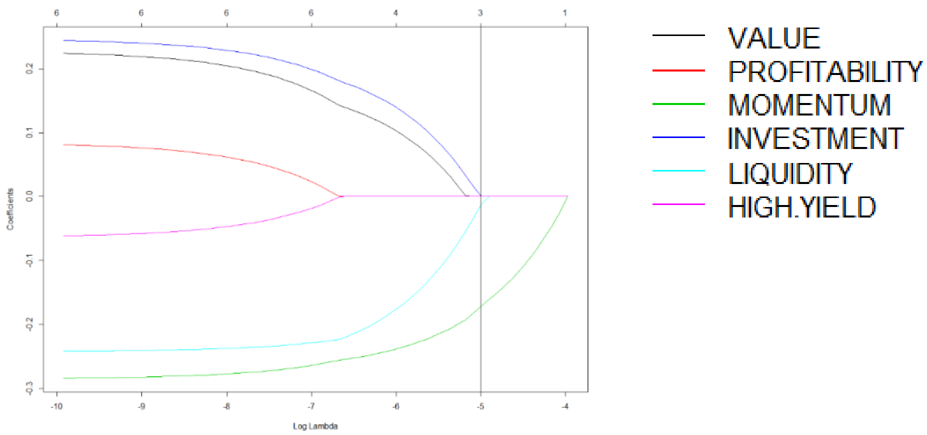
		1m	3m	6m	12m
EWMF	SWIX	6.36% (0.96)	6.06% (0.89)	1.4% (0.23)	3.68% (0.53)
	ALSI	7.16% (1.06)	6.86% (0.99)	2.2% (0.35)	4.48% (0.64)
FFPHW	SWIX	1.67% (1.74)	3.27% (0.44)	2.02% (0.27)	0.31% (0.26)
	ALSI	1.67% (0.26)	3.27% (0.44)	2.02% (0.27)	0.31% (0.04)

ANNEXURE J: LASSO REGRESSION

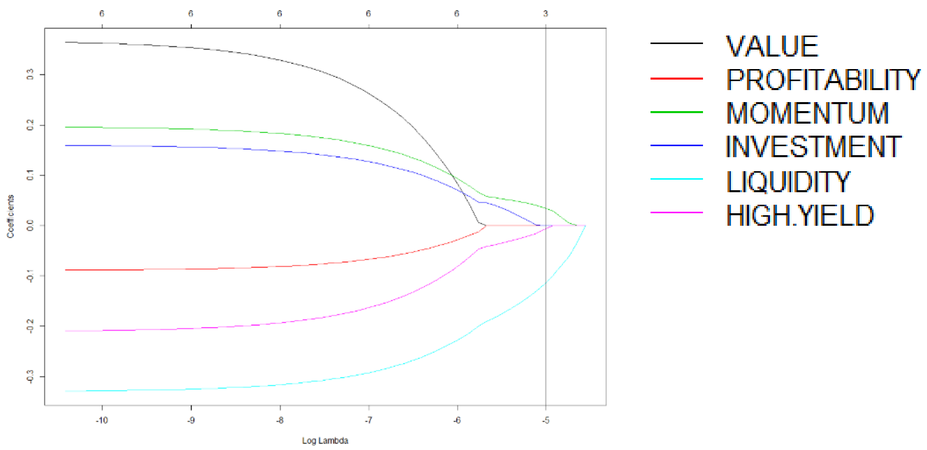
FFPHW winner annual rebalancing LASSO



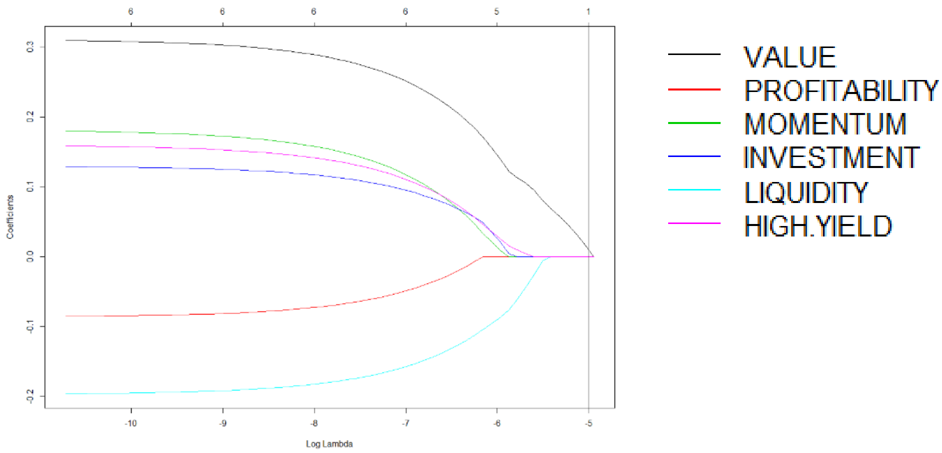
EWMF winner annual rebalancing LASSO



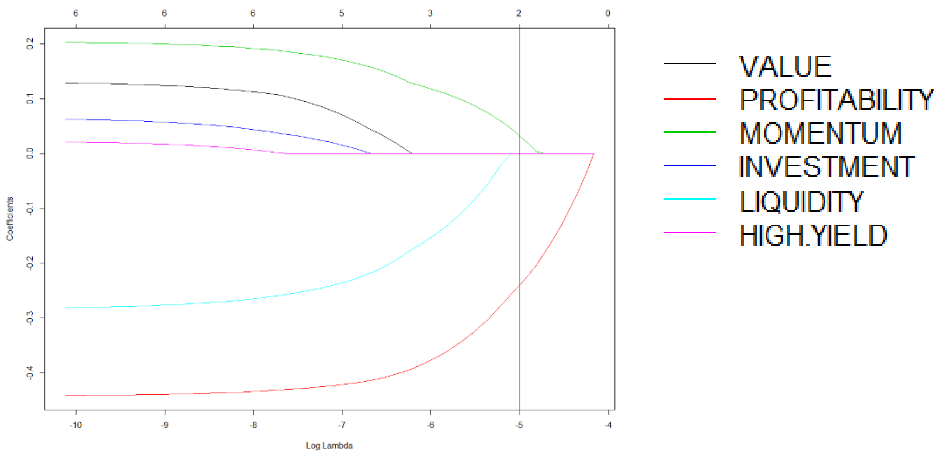
FFPHW winner semi-annual rebalancing LASSO



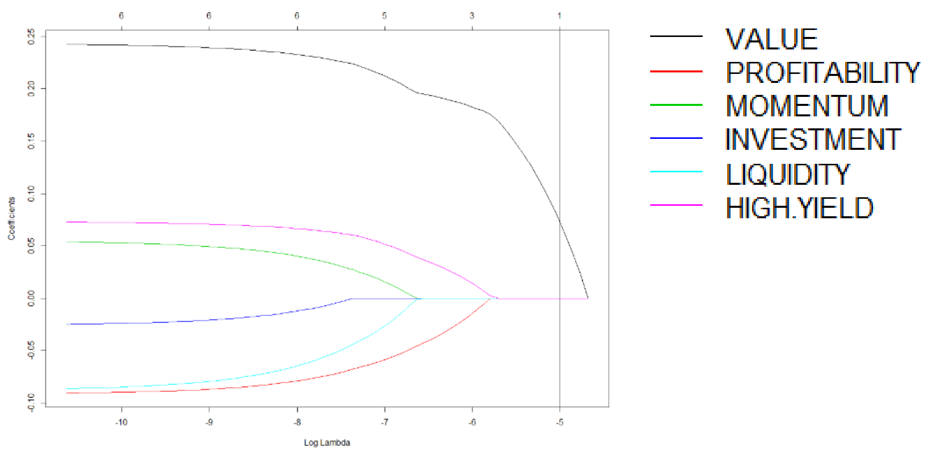
EWMF winner semi-annual rebalancing LASSO



FFPHW winner monthly rebalancing LASSO



EWMF winner monthly rebalancing



ANNEXURE K: CLASSIFICATION PERSISTENCE OF STOCKS

PANEL A: FIVE MONTH LOOK-BACK CLASSIFICATION PERSISTENCE (WINNER PORTFOLIO)

	FFPHW	EWMF	VALUE	PROF	MOM	LIQ	INV	HY
2007	0.83	0.52	0.95	0.96	0.79	0.96	0.9	0.96
2008	0.75	0.64	0.9	0.96	0.65	0.96	0.93	0.94
2009	0.61	0.63	0.9	0.96	0.54	0.97	0.9	0.93
2010	0.76	0.65	0.9	0.97	0.79	0.96	0.92	0.97
2011	0.7	0.52	0.94	0.97	0.66	0.97	0.91	0.95
2012	0.86	0.7	0.95	0.97	0.71	0.96	0.93	0.96
2013	0.8	0.64	0.92	0.98	0.72	0.96	0.91	0.96
2014	0.78	0.79	0.95	0.98	0.8	0.95	0.9	0.97
2015	0.75	0.74	0.95	0.96	0.69	0.94	0.9	0.97
2016	0.58	0.64	0.92	0.97	0.5	0.98	0.9	0.96

PANEL B: FIVE MONTH LOOK-BACK CLASSIFICATION PERSISTENCE LOSER PORTFOLIO

	FFPHW	EWMF	VALUE	PROF	MOM	LIQ	INV	HY
2007	0.78	0.88	0.95	0.96	0.76	0.97	0.88	0.96
2008	0.79	0.86	0.89	0.94	0.74	0.96	0.92	0.94
2009	0.77	0.82	0.92	0.95	0.53	0.96	0.92	0.92
2010	0.91	0.88	0.91	0.92	0.5	0.94	0.85	0.96
2011	0.84	0.89	0.95	0.96	0.67	0.97	0.95	0.98
2012	0.9	0.82	0.96	0.98	0.74	0.95	0.93	0.96
2013	0.83	0.86	0.95	0.96	0.69	0.98	0.92	0.97
2014	0.82	0.88	0.93	0.97	0.74	0.97	0.92	0.97
2015	0.77	0.9	0.96	0.97	0.8	0.97	0.9	0.98
2016	0.68	0.84	0.92	0.96	0.59	0.97	0.91	0.97

PANEL C: SIX MONTH LOOK-BACK CLASSIFICATION PERSISTENCE (WINNER PORTFOLIO)

	FFPHW	EWMF	VALUE	PROF	MOM	LIQ	INV	HY
2007	0.86	0.36	0.96	0.97	0.78	0.97	0.91	0.97
2008	0.74	0.58	0.89	0.96	0.69	0.97	0.93	0.94
2009	0.67	0.61	0.91	0.96	0.46	0.98	0.9	0.94
2010	0.82	0.61	0.9	0.97	0.76	0.97	0.91	0.98
2011	0.61	0.48	0.95	0.97	0.68	0.97	0.9	0.96
2012	0.87	0.68	0.95	0.97	0.65	0.96	0.92	0.97
2013	0.83	0.69	0.91	0.96	0.76	0.96	0.91	0.96
2014	0.79	0.95	0.95	0.98	0.82	0.97	0.9	0.96
2015	0.76	0.73	0.96	0.96	0.69	0.94	0.9	0.96
2016	0.56	0.59	0.92	0.97	0.53	0.99	0.89	0.96

PANEL D: SIX MONTH LOOK-BACK CLASSIFICATION PERSISTENCE (LOSER PORTFOLIO)

	FFPHW	EWMF	VALUE	PROF	MOM	LIQ	INV	HY
2007	0.78	0.92	0.95	0.95	0.75	0.97	0.87	0.96
2008	0.83	0.88	0.89	0.93	0.74	0.96	0.92	0.94
2009	0.8	0.85	0.93	0.96	0.53	0.96	0.92	0.93
2010	0.91	0.9	0.91	0.91	0.54	0.94	0.86	0.96
2011	0.86	0.88	0.95	0.96	0.71	0.97	0.95	0.98
2012	0.9	0.84	0.96	0.98	0.73	0.95	0.92	0.96
2013	0.84	0.86	0.95	0.97	0.76	0.98	0.91	0.97
2014	0.83	0.88	0.93	0.97	0.78	0.97	0.92	0.97
2015	0.82	0.9	0.96	0.97	0.82	0.97	0.9	0.98
2016	0.67	0.86	0.93	0.96	0.6	0.97	0.9	0.97

ANNEXURE L: CORRELATION OF LOSER PORTFOLIO NET RETURNS AND PORTFOLIO CHURN

CORRELATION OF NET RETURNS AND PORTFOLIO CHURN FOR LOSING PORTFOLIOS

	Portfolio	Net return
Churn	FFPHW	-32.10%
	EWMF	-3.33%
	VALUE	-4.48%
	PROF	-42.23%
	MOM	18.53%
	LIQ	15.12%
	INV	14.95%
	HY	-49.12%