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School of Finance and Tax

Market Timing on the Johannesburg Stock Exchange

by

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Abstract

The concept of market timing is hardly new. Theoretical work on the predictability of return stretches back for over a century, with substantial empirical work emerging from the 1960s onwards. This study aims to extend the literature by focusing on whether it is possible for an investor, utilising quantitative analytical techniques with available information, to utilise market timing to outperform the JSE ALSI.

Using the Johannesburg Stock Exchange All Share Index (JSE ALSI) as a proxy for equity market returns in South Africa, this study initially aims to determine whether there are significant relationships between independent variables and future returns, of differing horizons, between 1960 and 2010 and finds, using correlation analysis, several significant relationships.

These significant relationships are then included in multifactor forecast models, which are estimated using ordinary least squares regression. The findings from these estimations indicate that there is some, albeit small, portions of the market that is predictable by historic variables. Applying these forecasts to three trading strategies, this study finds that returns in excess of 6% above that of the JSE ALSI are possible.

However, there are several look-ahead biases that impact on this initial result. As the beta coefficients and the specification of the model (based on relational strength between variables) are determined based on the full sample of observations, it is possible that limiting the data such that it reflects only the information available to an investor at each point in time could lead to both differing coefficients and different specifications.

However, even when employing a dynamically updating model to eliminate these biases, there is still evidence of market predictability that can be profitably exploited, with an optimal combination of regression type, trading strategy and return horizon generating slightly less than 3% in excess of the JSE ALSI. Even incorporating transaction costs of 150 basis points of transaction value, it is found that it is possible to generate returns of 0.5% in excess of those of the JSE ALSI.

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Definitions and Abbreviations

All-Share Index (ALSI) – a market-capitalisation weighted index of stocks listed on the Johannesburg Stock Exchange.

Behavioural Finance – a school of Finance which posits that investors are not and do not approximate rational investors, but suffer from certain exploitable behavioural heuristics and biases.

Efficient Market Hypothesis (EMH) – the hypothesis that all available information is correctly priced into an asset, therefore only new information should move the price. This suggests that speculation will not yield excess returns.

Johannesburg Stock Exchange – a stock exchange based in Johannesburg, South Africa. It is the main South African equity market.

Market Predictability – the theory that there is a portion of future market movements that can be forecast by a knowledgeable investor based on information presently available.

Market Timing – a strategy where an investor invests in a risky asset when it is expected to increase in value and a risk-free asset when the risky asset is expected to decrease in value.

Trading Strategy – a system or set of rules whereby an investor determines their portfolio based on information that is available to them.

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1 Introduction

A multi-billion dollar financial industry has arisen from the belief that it is possible to consistently outperform the market. Investors such as George Soros have built empires based on correct forecasting. And yet, the theory of rational investment and efficient markets indicates that it is highly improbable to consistently earn returns in excess of a risk-adjusted required rate, as all public information should be incorporated into the price of an asset at any time (Fama, 1970). This theory suggests that the belief held by the financial industry is invalid and that George Soros is an outlier whose success is due to luck and not skill. And yet, investment banks like Goldman Sachs and JP Morgan Chase are able to rake in millions of dollars annually, with a large portion of this stemming from proprietary trading positions. It is this anomaly that provides the starting point of this study.

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1.1 Background

The generation of consistent outperformance requires some predictive ability of the investor. There are two methods in which these forecasts and consequent outperformance can be generated in an equity market: stock selection and market timing. Although both require forecasts, the actual method is different: with stock selection, an investor forecasts the returns of all equities in a market, or micro-forecasts, and picks the stocks that will generate returns in excess of the mean, weighted according to the construction of the market index; while with market timing, the investor is forecasting the market as a whole, or macro-forecasting, and switching between pure equity when the market is expected to earn positive returns and in a risk-free asset or in a short position of the equity when the market is expected to earn negative returns. Thus, stock selection focuses on the cross-section of returns, whereas market timing focuses on the time series of returns. It is market timing, or, more broadly, the use of forecasts of the market to generate outperformance, that forms the focus of this study.

Studies on market timing are hardly new. Treynor and Mazuy (1966), through analysis of characteristic lines of 57 mutual funds in America from 1953 to 1962, find that there is no statistically significant evidence of market timing ability. Sharpe (1975) determines that a manager requires to be correct roughly 75% of the time to merely match that of a pure buy-and-hold strategy of the S&P500. Merton (1981) develops a model, using option strategies, to determine the value of market timing, which is then followed by the development of statistical procedures that test for the presence of superior market forecasts by Hendriksson and Merton (1981).

It is the development of behavioural finance and the concept of predictable heuristics, coupled with empirical work by Campbell (1987), Poterba and Summers (1988), Jaffe and Mandelkar (1976) and Fama and French (1988a, 1988b & 1989) that provide evidence that market returns are at least partially predictable, indicating the possibility of market timers to be able to forecast the market accurately enough to generate excess returns. Later work by Pesaran and Timmermann (1995 & 2000) internationally and Keuler and Krige (2009) locally focus on the implementation of market forecasts to trading strategies, to determine whether these forecasts are exploitable.

It is this large body of empirical literature that provides the background to the research undertaken in this study.

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1.2 Research Objectives

The overarching objective of this study is simple: to determine whether a trader, employing quantitative analytical techniques (referred to as a 'quantitative trader' in this study) can, utilising publically available information, develop a forecasting model with sufficient predictive power that its forecasts can be implemented in a trading strategy that outperforms the market.

To achieve this, the study is broken down into more specific objectives. The first objective is to determine whether the market is predictable and, if it is, to what degree. This is achieved by an analysis of the correlations between various possible predictor variables and that of the

Johannesburg Stock Exchange (JSE) All-Share Index. These relationships are then used to develop a multivariate forecast model through ordinary least square regression analysis. In the absence of significant relationships, one could conclude that the ALSI is not predictable.

However, if statistically significant relationships are found, the second objective is to determine whether these forecasts can be converted into an exploitable market timing strategy. To achieve this, trading strategies are created based on the forecasts of the multivariate model and the performance of these strategies are compared against a pure buy-and-hold strategy of the market. These forecasts are initially generated from an analysis of the full sample of data. However, a hypothetical investor at each point in time will not be able to derive relationships and coefficients utilising the full sample of data, and therefore, this initial study needs to be adjusted to better proxy the investing decision of a quantitative trader incorporating publically available information in a forecasting model. To achieve this, the initial methodology is repeated through time, but limiting the data such that it reflects only the information available to the investor at that point.

Finally, if there is evidence of exploitable market predictability, the impact of transaction costs on this outperformance is analysed.

1.3 Contribution

Although there has been extensive research into market predictability and its exploitability, this study aims to extend the literature in several aspects. It firstly aims to provide an analysis of the relationship between a comprehensive set of potential predictor variables and the equity market in a South African context. It secondly aims to model the dynamically updating analysis of information to proxy the incorporation of information by a quantitative trader and the returns that can be yielded from this process. It finally aims to determine the outperformance that is created by using a definition broader than that of strict market timing, namely, where forecasts are utilised in weighted strategies that do not switch purely between risky and risk-free asset, or allows an investor to take a short position against the market when forecasts suggest market

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declines. The first variation on the traditional view of market timing may provide a smoother pattern of returns, due to partial weighting in both asset types, and therefore a superior risk-return profile, while the second variation, by allowing an investor to profit proportionately from a correctly forecasted market decline, may lead to greater absolute returns.

1.4 Dissertation Organisation

This study is organised as follows:

Chapter two provides an overview of the Johannesburg Stock Exchange All-Share Index, focusing on trends, variability and risk through time. It also analyses the potential of market timing within the market.

Chapter three provides an overview of the literature. The first section focuses on the theoretical aspect of returns and returns predictability. The following sections focus on empirical evidence supporting and refuting market predictability.

Chapter four summarises the data and variables chosen and provides an overview of the methods that are utilised to meet the objectives set out for this study.

Chapter five analyses the individual predictor variables, their relationship with the market, and their suitability for inclusion into an ordinary least square regression multivariate forecast model.

Chapter six then estimates this multivariate forecast model and utilises its forecasts to generate three trading strategies. The performance of these strategies against a pure buy-and-hold strategy of the market is analysed to determine whether market predictability is indeed exploitable.

Chapter seven augments the model in chapter six by including implicit forecasts generated by long-term return forecasts in shorter return horizons, before applying the new forecasts to the three trading strategies in chapter six to determine the impact of implicit forecasts in strategy performance.

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Chapter eight extends the work in chapters six and seven by limiting the information at each point in time to only include what would be known at that point by a hypothetical investor. The multivariate model that would be selected based on this information set is then estimated and its prediction used to determine the forecast of the investor. These forecasts are then implemented into the three trading strategies utilised in chapters six and seven. It also analyses the impact of transaction costs on the performance of these strategies.

Finally, chapter nine provides a summary of the results and the implications of these findings, as well as discussing possible future extensions to this study.

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2 Overview of the Johannesburg Stock Exchange All-Share Index

The Johannesburg Stock Exchange (JSE) was founded in 1887, mainly as a tool to raise capital to mine the recently found gold fields in the then Transvaal Republic (Firer, Ross, Westerfield & Jordan, 2004). From these humble beginnings, the JSE had grown to the 22nd largest stock exchange in the world by 2002 (Firer et al., 2004). Throughout this period, the value of the JSE as a whole has fluctuated, in what would appear to be a random fashion, from high to low, with only a long-term upward trend being visible. And although some of these movements may indeed be due to unmerited speculation, many movements can trace their genesis to an underlying social, political or economic event.

This chapter of the study aims to provide an overview of the market, using the JSE All-Share Index, a market-capitalisation weighted index of all the shares listed on the JSE (market-capitalisation free float weighted index after 1 July 2002), as a proxy of the market for South African equities, focusing on trends, sharp movements and the general pattern of returns that have occurred during the sample period.

Unfortunately, a full history of the JSE ALSI and potential predictor variables is unavailable. As such, the overview begins with the earliest available data point of January 1960, with the sample ending in January 2010. Because data from a total return index only begins several decades later, a proxy for a total return index is constructed by adding one twelfth of the dividend yield (approximately converting an annual dividend yield to a monthly dividend yield) to monthly returns.

The JSE ALSI has historically provided strong returns, with an annualised average of 17.22% over the sampled period. In contrast, a risk-free asset, using the long-term gilt rate as a proxy,

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yielded an average annualised return of 11.52% from 1965 – 2010. A cursory look at those two statistics suggests that the JSE ALSI has a risk-premium of 5.7%. However, the JSE ALSI is also subject to some extreme returns, with the most extreme, a one-month return of 16.63% occurring in December 1973 and a one-month loss of 34.71% in August 1998, highlighting the large one-month movements that can occur on the JSE ALSI.

Although statistics can provide an idea of the trend and the volatility of returns, they do not provide a measure of the pattern of returns and, as such, a figure is presented below so that the variations of returns can be analysed.

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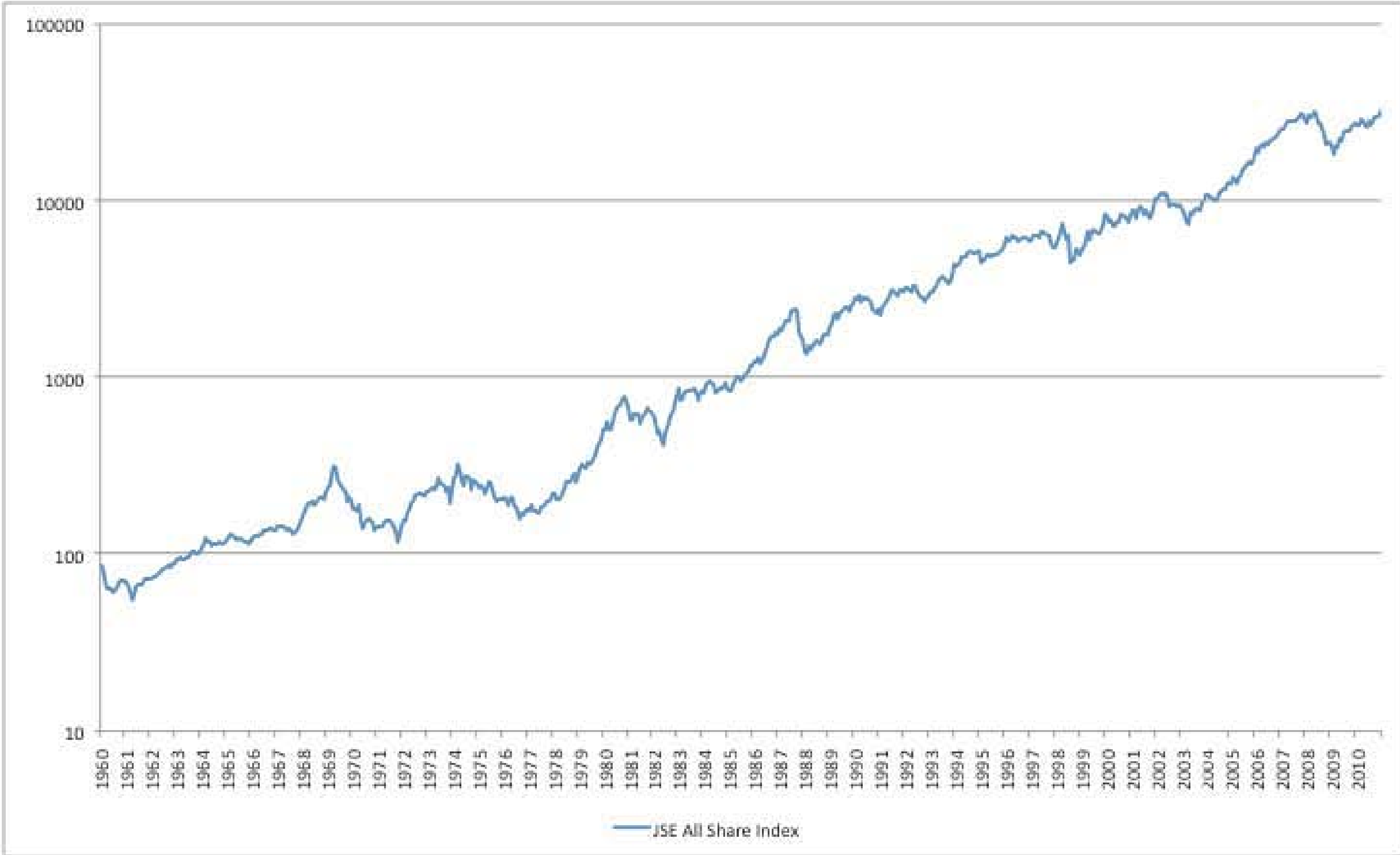
Figure 2.1 JSE All Share Index from 1960 – 2010 (Log Scale)



It is clear from the above figure that the JSE ALSI has an upward trend, as expected given the large positive average. However, it is equally clear from the above figure that the JSE ALSI does not grow in a linear pattern, with periods of accelerated growth and losses present.

The beginning of the sample shows negative returns for several months before a long-term upward trend is visible. From 1967, this trend is replaced by a period of accelerated growth before a crash in 1969. This crash leads to negative returns for roughly two and a half years, with the upward trend in the following two and a half years bringing the JSE ALSI in line with its 1969 value. Following this recovery, there is a stable downward trend in the JSE ALSI for approximately two and a half years. One would think that there was a consistent pattern of a two and a half year upswing followed by a two and a half year downswing, but the JSE ALSI showed its unpredictable nature as the period from 1976 to 1980 was characterised by strong positive returns. However, this period of growth in the value of the ALSI was followed by a two-year downward cycle. But the ALSI bounced back strongly at the end of 1982 and the market experienced fairly stable positive returns for the next several years. These stable returns increased in magnitude from 1985 onwards, until much of the value generated in the previous two years was destroyed by the 1987 Black Monday crash on Wall Street and its repercussions. After this crash, the market grew in a fairly stable fashion, punctuated by crashes in 1998, 2002 and, most recently, in 2008. Despite these crashes, the pattern of returns after 1985 in this period could be characterised as less volatile. To further test this hypothesis, the sample is broken into two subsamples: one from 1960-1985 and the other from 1985-2010. Although the average returns are the same for both subsamples, a visual analysis allows one to observe the character of returns in the two sample periods.

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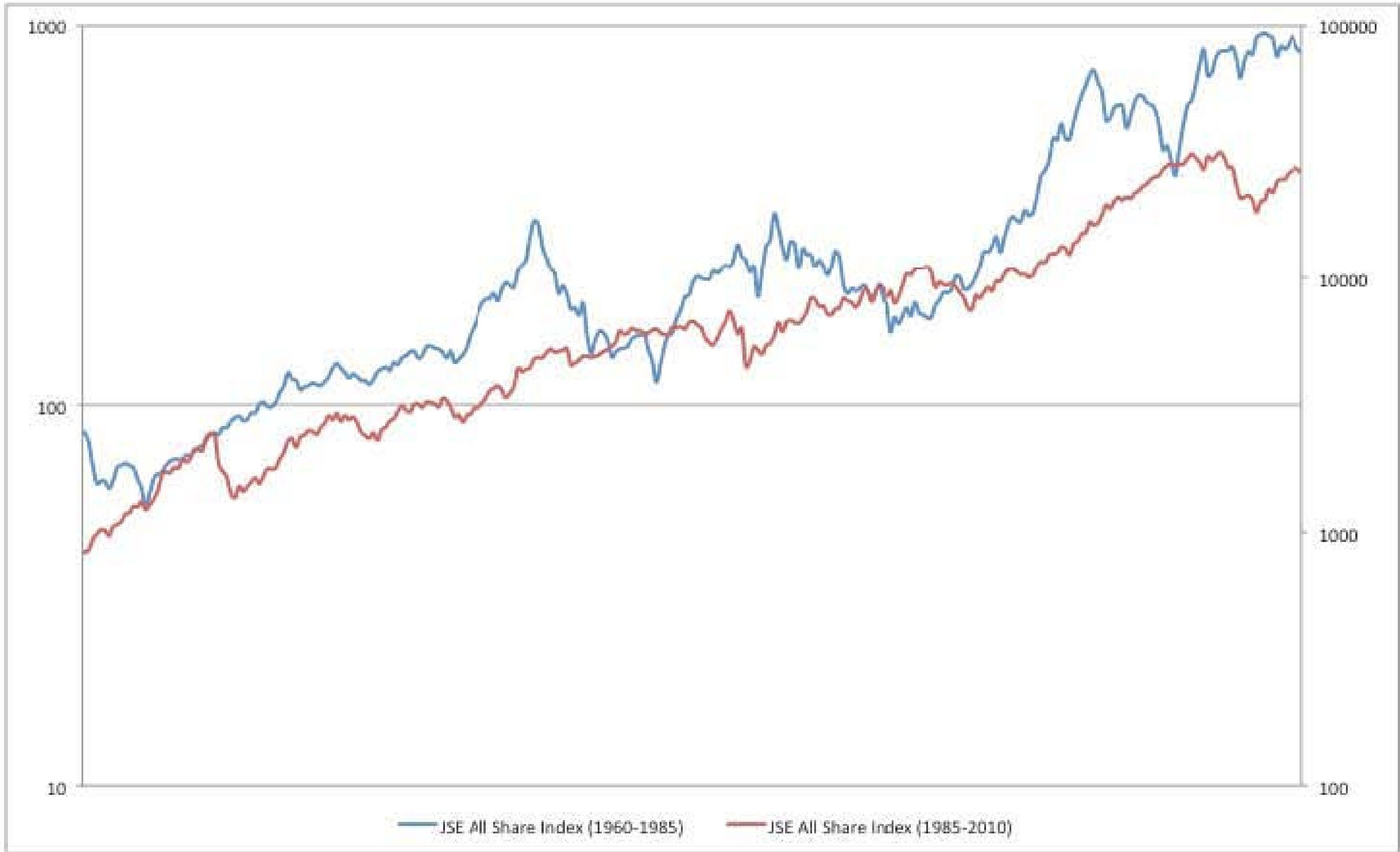
Figure 2.2 JSE All Share Index Subsamples from 1960 – 1985 and 1985-2010 (Log Scale)



It is clear from the above that the JSE ALSI after 1985 has less extreme movements in a direction. This would suggest that the market has become relatively more stable in this time. There could be many plausible explanations for this, from an increase in size to the JSE ALSI to increased foreign investment in South African equity; however, these go beyond the scope of this study. However, it is clear that the return pattern of the JSE ALSI is not constant or linear, and that even the volatility of returns itself is not stable.

As a result of the above overview, it is clear that the rate of return for an investor is highly dependent on when they enter and exit. For example, an investor who invested at the beginning of September 1967 and exited at the end of April 1969 would have earned a return of 142.78% over the period, an annualised return of 70.27%. However, if an investor entered the market at the end of the previous sample, at the beginning of May 1969, and exited on October 1971, they would have earned a return of -61.65% over the time period, an annualised loss of roughly 31.84%.

Although these are two extreme cases, and there are many periods where the JSE ALSI grows in a fairly stable fashion, it is still imperative to discuss these extremes. And as most investors are more concerned about downside losses than upside gains, it is useful to analyse the drawdowns that occurred in the market through the sample period.

The most extreme drawdown, in terms of magnitude, has already been discussed in the example above. It also occurred during the longest drawdown in the sample period, beginning at the start of May 1969 and ending at the end of February 1974. Thus it took fifty-eight months for the investment of an individual who invested at the beginning of the period to have an increase in value of their initial investment. However, this is not an atypical occurrence. One-month after the market reached its April 1969 value, in April 1974, it entered another drawdown that lasted fifty-three months, with a loss of 47.75% at the trough, an annualised loss of 32.27%. There was another drawdown between October 1980 and October 1982, exactly two years, with a trough of 42.57% in June 1982. It took the market twenty-three months to recover after September 1987, although much of this is attributable to Black Monday in October 1987, where the market lost 26.87% in one month. It also took the market nineteen months to recover to its April 1998 value, although much of this was also attributable to one month, August 1998, which was due to the Asian and Russian financial crises. And the JSE ALSI had still

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not recovered to its May 2008 levels by the end of the sample period, mostly due to the lingering effects of the subprime crisis.

In total, there were a total of forty-five drawdowns that lasted more than a month, with nine drawdowns that lasted between three months and six months, nine that lasted between six and twelve months, four that lasted between twelve and twenty-four months, and five that lasted for a period greater than twenty-four months, with the average drawdown lasting 9.51 months.

Although the above suggests that the JSE ALSI is a highly risky market, there is also the case of positive returns. There have been periods of continuous monthly JSE ALSI growth, with the period from May 1982 to January 1983 yielding a return of 80.33% in seven months without one negative monthly return. In total, there were fifty-seven occasions when the JSE ALSI had consistently positive returns for more than one month, with fourteen lasting between three and six months, seventeen lasting longer than six months, and the longest lasting seventeen months. On average, when the market moved in a positive direction for more than one month, there were consistently positive returns for 6.14 months.

Although the market is volatile, an investor could, hypothetically, avoid losses by moving into a risk-free asset just before the market experiences losses. So what return would this investor, born with perfect foresight, earn if they were only invested in the market during periods of positive returns, and in a risk-free asset when the market experiences negative returns, assuming that the ninety-day bankers' discount rate provides an accurate proxy of the returns generated by a risk-free asset? A caveat must be added to this answer, as the sample for this analysis only begins in 1965, as there is an unavailability of data for the proxy on the I-Net Bridge database, and frictions such as transaction costs are ignored, but simplistically, it is still a staggering annualised return of 51.19%. And the return if the perfectly prescient investor chose to rather short the market instead of buying into a risk-free asset when the market declines is an annualised 170.08%.

Although these answers do not include real-world fees and costs, they provide clear evidence that there is potential value in the ability to accurately forecast market movements. However, there are also clear risks when an investor incorrectly believes they can forecast the market. To illustrate this danger, the portfolios of three

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hypothetical investors are created with the assumption that they have no predictive ability and, as such, a flip of a coin can proxy their decision to hold either the JSE ALSI or the risk-free asset in scenario one and long the JSE ALSI or short the JSE ALSI in scenario two. Their annualised average return over the time period is tabulated below, along with the annualised average return of the JSE ALSI.

Table 2.1 Annualised Average Returns of Hypothetical Investors

	Investor 1	Investor 2	Investor 3	JSE ALSI
Scenario One (JSE ALSI/Risk-Free)	15.28%	10.66%	12.65%	14.72%
Scenario Two (Long/Short)	1.77%	-6.10%	-3.50%	14.72%

The returns of investors 1, 2 and 3 are constructed using randomly generated forecasts applied to a strategy that switches between the JSE ALSI and a risk-free asset dependent on whether the forecasted return on the JSE ALSI is positive or not respectively. Returns are averaged annualised returns. Sample Period: January 1965 – January 2010.

Out of the three investors, only investor 1, investing in either the risk-free asset or the JSE ALSI, is able to generate a return in excess of the return generated by the JSE ALSI, although this excludes frictions such as transaction costs. The other two investors' attempt to generate excess returns fail in both scenarios, while investor 1's attempt to generate excess returns by either being long or short in the JSE ALSI fails. It is also clear that, across all three investors, their implementation of their 'forecasts' in scenario two yields returns that are worse than the returns they would have generated in scenario one, or in a pure buy-and-hold of the JSE ALSI.

Clearly both of the cases described above are extremely naïve. It is highly improbable to find an investor with perfect foresight, just as it is highly improbable to find an investor who would base their investment strategy purely based on a flick of a coin. Investors will, in general, analyse the data that is publically available in an attempt to gain some foresight of market movements, and the stronger their ability to convert this data into accurate forecasts, the greater the likelihood that they will find excess returns.

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3 Theoretical Overview and Overview of Prior Literature

This chapter provides an overview of available literature relating to the ability of an investor to predict market movements. It is broken into two sections. Section 3.1 provides an overview of the theories linking current information to future returns. Section 3.2 then analyses the empirical tests of each element of the theory.

3.1 Overview of Theory

The theory reviewed below can be broadly decomposed into two categories. The first is that of the efficient markets, where prices fluctuate around their true, or intrinsic value, and the return that an investor will receive on average is the required rate of return, generated by some rational pricing model like Gordon's dividend discount model. The second is that of behavioural finance, where there are predictable heuristic biases inherent in investment decisions which cause phenomenon that do not fit that of a rational investor, such as short-term momentum and long-term mean-reversion.

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3.1.1 Rational Investors and Return Predictability

There is a large body of theoretical work on the predictability of share returns. One of the earliest examples is Jules Regnault's 1863 study, "Calcul des Chances et Philosophie de la Bourse," which posits that, in the absence of new information, the intrinsic value of a stock remains unchanged (Davis & Etheridge, 2006). Therefore, any price fluctuations are due to transactions driven by speculative expectations, implying that share prices increase or decrease with equal probability (Jovanovic & Le Gall, 2001). This is the origin of the theory of random walks in asset returns, whereby future returns are independent of past returns (Fama, 1970). However, the theoretical derivation of this finding is lacking, although Regnault finds some empirical backing to his theory (Davis & Etheridge, 2006).

It is thirty-seven years later, in a doctoral thesis by French mathematician Louis Bachelier, that a mathematically rigorous derivation of the random walk theory is established (Davis & Etheridge, 2006). Bachelier, initially focusing on French stocks, formulates that the expected return of a speculator is zero by assuming that the expected price of an asset follows a martingale process, where the price itself follows a continuous Markov process that is homogenous in time and space and determining that the distribution is Gaussian in nature (Courtault, Kabanov, Bru, Crépel & Lebon, 2000; Davis & Etheridge, 2006). He then derives the same law by considering the price process to be a limit of random walks, before extending his mathematical principles to arrive at similar conclusions regarding the type of options that are available at the time (Courtault et al, 2000).

Despite the conclusions of this study and its use of stochastic techniques to solve problems relating to financial economics, it remains relatively unknown until the mid-1950s, when a statistician, Jimmy Savage, informs several prominent economists of its existence (Davis & Etheridge, 2006). For Paul Samuelson's 1965 study, "Proof That Properly Anticipated Prices Fluctuate Randomly", it provides the tools he required to provide some theoretical framework to the rapidly growing empirical literature on the random walk of stock prices. Samuelson initially focuses on the distribution of spot price of any tradable asset and assumes that the probability of the spot price of an asset as the sum of the different, mutually exclusive probabilities that could lead to that price occurring. With this general, but relatively unrestrictive assumption in place, Samuelson then focuses his study on the sequence of prices of a future from inception to closure. Samuelson then assumes that all buyers and sellers utilise all available information at a point in time to determine the price of the spot price at the expiration of the future, and price the future at this expected spot price. With these two assumptions in place, he shows that, irrespective of the probability distribution of the underlying spot price, the expected price follows a martingale process with an expected return of zero, thereby indicating that all available information has already been priced correctly into the future price. Following from this, as the price updates to new information, actual prices fluctuate around the expected price, and therefore returns fluctuate randomly around a mean of zero, implying that there is no technical or mathematical tool that can be used that can predict future returns and therefore generate consistent profits. These results hold irrespective of the distribution of the underlying asset. Samuelson then adjusts the initial martingale process to include the rate of return required by the investor, thereby changing the initial assumption such that the price of the future is equal to the expected price of the spot discounted to the present. Thus, based on the earlier work, the expected return of the investor is the required rate of return,

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with actual returns fluctuating around this rate, implying that an investor cannot use a method to consistently generate returns in excess of the required rate.

Samuelson's study therefore provides a theoretical framework around the expected returns of future pricing following expected spot prices, but he does not delve deeper into the pricing of the underlying spot prices besides assuming that they follow some probability distribution. It is Fama's (1970) seminal study, "Efficient Capital Markets: A Review of Theory and Empirical Work," that provides an overview of the theoretical and empirical work on the characteristics of asset returns. The underlying principle is that, "in an efficient market, competition among the many intelligent participants leads to a situation where, at any point in time, actual prices of individual securities already reflect the effects of information based both on events that have already occurred and on events which, as of now, the market expects to take place in the future" (Fama, 1965b: 56), such that $E\left(\overline{P}_{j,t+1} \mid \theta_t\right) = \left[1 + E\left(\overline{R}_{j,t+1} \mid \theta\right)\right] P_{j,t}$, where P is the price of asset j at time t + 1, R is the one period return of asset j from t to t+1, θ is the information content at time t, and the bar indicates that $P_{j,t+1}$ and $R_{j,t+1}$ is a random variable at time t (Fama, 1970). This implies that the actual market price is an accurate approximation of the intrinsic, or true, value of an asset. The expected return of the asset given information at time t will then be derived according to which expected return model is assumed to apply. However, this principle requires further description to make testing its validity tractable. Fama (1970) therefore creates three forms of market efficiency: weak, semi-strong and strong efficiency. In weak-form efficiency, returns are independent of their history. Therefore, if returns follow a random walk with a trend equal to the required rate of return, the market is weakly efficient. In semi-strong efficiency, the market updates prices to reflect any new information, and is testable through event studies. Finally, in strong form efficiency, even private information is correctly valued in the price of an asset. Reviewing the empirical literature available at the time, Fama (1970) finds strong evidence that the market displays weak and semi-strong efficiency, with limited evidence suggesting strong-form efficiency.

Although efficient markets lean on the estimations of intrinsic value by market players, there are many methods in which intrinsic value can be estimated. One of the earliest and most well-known is Gordon's dividend discount model, originating from Myron Gordon's 1959 study, "Dividends, Earnings and Stock Prices." Gordon assumes that an investor prices a stock by calculating the present value of future cash flows. For an investor with

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the aim of holding the stock for one period, there are two cash flows, any dividend payments and the price they sell the stock for in the next period, and therefore the price they should be willing to pay is derived as $P_0 = \frac{D_1 + P_1}{\left(1 + r_{0,1}\right)} = \frac{D_0\left(1 + g_{0,1}\right) + P_1}{\left(1 + r_{0,1}\right)}$, where D_1 is the dividend paid one period in the future, P_1 is the price of the stock one period in the future, $g_{0,1}$ is the growth of dividends from period 0 to period 1 and $r_{0,1}$ is the required rate of return from period 0 to period 1. However, the price of P_1 can also be derived using the same formula, such that $P_1 = \frac{D_1\left(1 + g_{1,2}\right) + P_2}{\left(1 + r_{0,1}\right)}$. Therefore the price at time 0 can be written as $P_0 = \frac{D_0\left(1 + g_{0,1}\right)}{\left(1 + r_{0,1}\right)} + \frac{D_0\left(1 + g_{0,1}\right)\left(1 + g_{0,2}\right) + P_2}{\left(1 + r_{0,1}\right)\left(1 + r_{1,2}\right)}$. Substituting in for every value of P_t, and assuming that both the required rate of return and the growth of return remain constant through time, the price at time 0 can be derived as $P_0 = \frac{D_0\left(1 + g\right)}{r - g}$. This can be rearranged to determine the required rate of return, such that $r = \frac{D_1}{P_0} + g$, or, as dividends grow constantly, $r = \frac{D_0(1 + g)}{P_0} + g$. This derivation of the formula thus provides one determinant of the required rate of return.

Simplistically, this formula breaks the rate of return into two components: the forward-looking dividend yield and the growth rate in dividends. Although Fama (1970) indicates that an investor should not be able to generate profits in excess of the required rate of return, this discount model provides an investor with an estimation of the expected rate of return that an asset should yield. Thus, conceptually, an investor can forecast their return through the use of a dividend yield and an accurate estimation of the growth prospects of the underlying asset. If one assumes that a firm has a continuous retention ratio of earnings, b, this formula can be extended, such that the required rate of return is a function of earnings, whereby $r = \frac{(1 - b)E_0(1 + g)}{P_0} + g$. This extension indicates that the required return is a function of the earnings yield, retention ratio and growth rate. Thus, the conclusions that can be drawn from Gordon's pricing model is that both dividend and earnings yield provide, theoretically, an indication of the rate of return that an asset should yield.

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3.1.2 Behavioural Finance and Return Predictability

However, the theory of markets being efficiently priced hinges on two assumptions: investors make decisions based on expected utility theory and that their forecasts are unbiased (Thaler, 1999). Although this is extreme in practice, the presence of investors who do not meet these criteria can still lead to efficient markets, as long as the marginal investor is rational (Thaler, 1999). The efficient market theory assumes "when irrational optimists buy a stock, smart money sells, and when irrational pessimists sell a stock, smart money buys, thereby eliminating the effect of the irrational traders on market price" (Shiller, 2003: 96). However, it requires that the impact of the rational investor offsets the impact of the irrational investor. Thaler (1999) uses an example of a two asset market where one asset is overvalued relative to the other and determines that there are five conditions that must occur for this to occur: there cannot be too many non-rational investors; short selling must be costless so that rational investors can drive overvalued stocks downwards; only rational investors can short stocks, otherwise the non-rational investors can drive the undervalued stock down further; the actual relative values of the two assets must be realised by all investors at some point in the future; and finally, the rational investors must have long enough horizons such that they plan to be invested when the true relationship between the two assets is established by all investors. However, the conditions are clearly not met in the case of the Royal Dutch/Shell Group, where each asset is listed separately and which interests are merged in a 60/40 split; however, the ratio between the two does not follow that split and even taking into account the effects of tax and transaction costs, this finding cannot be explained while asserting that the rational investor is the marginal investor (Thaler, 1999).

Another possible anomaly from the notion of the rational investor comes from that of the feedback model (Shiller, 2003). This observation is not particularly new, with Charles MacKay in 1841 noting the phenomenon (Shiller, 2003). The principle is fairly simple: when prices of an asset rise, other investors observe potential gains that can be realised from this asset, and also buy into it. This behaviour causes a positive feedback, causing the price of the asset to increase, causing additional feedback. The inverse can also occur when there is negative feedback. As a result of this behaviour, asset prices can have large deviations from the notion of fair value (Shiller, 2003).

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It is these anomalies that suggest the theory of rationality does not fully encompass the actuality of the market. As a result, there is a movement away from 'classic finance', where investors are assumed to be rational, to behavioural finance, where it is assumed that there are large bodies of investors who, although attempting to be rational, make fairly predictable mistakes, based on certain heuristic biases (Thaler, 1999). Thus, behavioural finance focuses on the psychology of investors and how their beliefs can influence markets.

It is the impact, and not a description, of these heuristic biases that is useful to the objectives of this study (Barberis & Thaler (2003) provide a comprehensive overview of these biases, as well as of behavioural finance as a whole). One of the principles of efficient markets, as explored above, is that rational investors will cause prices to fluctuate around intrinsic values. However, if one assumes that there are irrational investors who are all essentially feedback traders (buy when the price has gone up, sell when the price has gone down) in large enough quantities that they can influence prices, and that rational investors are aware of their presence in the market, then, when good or bad news affects the intrinsic value of the stock, rational investors will buy or sell in excess of the amount assumed by efficient markets, due to the fact that they are aware that the price movements caused by their trades will cause the irrational, feedback investors, to move prices further (De Long, Shleifer, Summers & Waldmann, 1990). Therefore, rational investors will amplify the feedback effect.

Another anomaly found in the empirical literature is that there is short-term market under-reaction, causing a momentum effect, and long-term market over-reaction, causing a mean reversion effect. Barberis, Shleifer and Vishny (1998) explain this based on two behavioural heuristics: conservatism, where an individual is more likely to cling onto original beliefs, despite evidence suggesting that they may be incorrect; and representativeness, where an individual attempts to describe an object or event by its similarity to another known object or event. The latter heuristic provides a psychological explanation as to why individuals believe they observe patterns in randomness. To model these heuristics, they assume that there is one asset and a representative investor that holds consensus earnings forecasts on this asset and price it based on this forecast. They also assume that earnings follow a random walk; however, this representative investor believes that earnings are either in a trend state, whereby the direction of returns continue to remain positive or negative dependent on the direction of prior returns, or in a mean-reverting state, whereby the direction of returns is opposite to prior returns. Finally,

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an investor believes that the asset is more likely to stay in its previous state than to switch to the other state. Assuming that an investor believes that earnings are in a mean-reverting state, the investor will believe that a positive earnings shock should immediately be followed by a negative earnings shock, and vice versa. If this mean-reversion does occur, the realised return is not large as the market has expected this, and already priced it in. However, if it doesn't occur, there is a large realised return, in absolute terms, due to the surprising (to the investor) nature of this event. This therefore causes a short-term momentum effect. If the investor assumes that earnings are in a trend state, when the trend eventually stops, the investor is taken by surprise by the news, assumes that earnings are now in a mean-reverting state and, due to the prior trend, are therefore distant from their means, and causes large movements in price in the opposite direction of the prior trend. This therefore provides a psychological theory as to the cause of the long-term mean-reversion of prices.

Hong and Stein (1999) provide an alternative explanation to the short-term momentum effect and long-term price reversion. Instead of focusing on the heuristics of the representative investor, they focus on the interaction between traders with individual limitations to the price generating process. They assume that there are two types of traders: newswatchers, who generate pricing forecasts based solely on fundamentals, and momentum traders, who generate pricing forecasts based solely on historic prices. A final assumption is that private information diffuses slowly amongst the newswatchers. Thus, if there were only newswatchers in the market, there would tend to be under-reaction to new information, as the information slowly diffuses across investors. However, if there are momentum traders, any trend that occurs from trades implemented by the newswatchers (such as price increases when an asset is below its fundamental value), is amplified by these additional traders, who take any movements as an indication of a trend being formed. Thus, in the short-term, momentum traders directly push prices in the direction of the initial price movement. However, if the momentum traders push the price too far, the asset will be priced above fundamental values, and when the newswatchers become aware of this, they slowly drive prices down. Momentum traders observe this, thereby pushing prices more rapidly to their fundamental value. Thus, the newswatchers cause short-term under-reaction to changes in fundamental changes. The momentum traders then amplify the movement to fundamental value and may cause the market as a whole to over-react to information, if prices are pushed above fundamental equilibrium prices.

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3.2 Empirical Tests of Return Independence

The previous section provides an overview of the theories that link historic information and returns. However, it is essential that these theories be tested with real-world data to assess their validity. The above provides an overview of the empirical literature on return predictability.

3.2.1 Short-Term Historic Returns

According to the efficient market hypothesis, if the market is weak form efficient, there should be no short-term momentum effects. However, theories of behavioural finance presented in the previous section indicate the presence of short-term momentum, assuming certain heuristic biases. To determine the validity of each theory, the below provides an overview of the literature that focuses on the nature of the relationships between short-term historic returns with future short-term returns.

Empirical studies supporting the theory of efficient markets are in existence before 1965. Kendall (1953, cited in Fama, 1970) examines the serial correlations of British industrial share indices weekly changes, and concludes that no clear relationship can be found. In 1961, Alexander (cited in Fama, 1970), provides one of the earliest examples of testing trading strategies, utilising a stock selection methodology. He initially constructs a "y% filter", where a short position is reversed to a long positions when a stock has risen a certain percentage from its last low and a long position is reversed to a short position when a stock has declined by a certain percentage from its last high. He then uses this y% filter to construct an investment strategy and compares its returns to that which would have been yielded by an investor who used a buy-and-hold strategy for the same period. If the returns of the filtration strategy are higher than that of a buy-and-hold strategy, then it would suggest that this form of technical analysis is able to predict future returns, implying that past prices can be used to predict future returns and that shares do not follow a random walk. However, Alexander (1961) initially finds no evidence supporting this, and when he adjusts his methodology in 1964 to correct some biases, he again reaches the same conclusion. Although this was a highly specific study, it provides early evidence that technical trading strategies designed to outperform the market are ineffective (Fama, 1965a), and paves the path to many new studies on trading strategy performance.

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Eugene Fama (1965a) tests whether daily stock prices follow a random walk process, which can be inferred if the fluctuations in price are independent of prior fluctuations. He tests this hypothesis using serial correlations of price changes and runs on price change sign stability on stocks listed on the Dow-Jones Industrial Average. The results suggests independence in the majority of cases, with only several individual shares suggesting otherwise, and with the dependence of returns in these shares being very small. He also tests whether there may be dependence for non-daily differencing intervals, by repeating his methodology with four, nine and sixteen day differencing intervals. The results are similar to those for daily differencing, although there is less contradictory evidence against independence of returns for longer differencing intervals. With this rigorous evidence of serial independence, Fama is able to conclude that it is likely that the markets follow a random walk process, making forecasts of future returns based on current and prior prices unlikely.

However, contrary to the above literature, Poterba and Summers (1988), using index returns on the NYSE, find that the return variance on one month-returns is only 0.79 times as large as the one-month variance implied from one-year returns, suggesting that there is positive autocorrelation in monthly returns. These findings hold not only in America, but also in fourteen out of fifteen additional countries incorporated in their analysis. In a later study, Cutler, Poterba and Summers (1990) find that, in thirteen equity markets, there is evidence of statistically significant autocorrelation in one-month and twelve-month returns. These findings provide evidence of a momentum effect in market prices, a finding contrary to that of Fama (1965a).

In summary, although there is suitably strong evidence for the independence of returns in daily returns, there is also suitably strong evidence of autocorrelation, and therefore momentum effects, in monthly returns.

3.2.2 Tests of Serial Independence in Long-Term Returns

Behavioural finance posits that, in the presence of short-term momentum, there will be an eventual over-reaction, after which prices revert to their means. The below focuses on the relationship between historic returns and long-term future returns.

One of the initial studies examining long-term returns is that of Summers (1986), which tests whether an absence in the autocorrelations of short-term returns implies that all historic returns lack forecasting power. He assumes a contrary position, namely that markets exhibit mean-reverting tendencies after large, temporary movements away from intrinsic value, and theoretically exhibits that tests for autocorrelation of short-term returns do not reject the null hypothesis that markets are serially independent, even if there is significant negative autocorrelation in 3-5 year returns.

However, Summers' (1986) study only presents a theoretical challenge of the statistical techniques in use at that time, but does not provide empirical proof that markets are mean-reverting in the long-run. It is Poterba and Summers (1988) who find evidence of negative long-term autocorrelation. Using absolute and excess returns on the NYSE between 1926 and 1985, they find that return variance for eight-year returns are only four times more variable than one-year returns, instead of the implied eight times. The study then expands its analysis to fifteen additional countries. Long-term negative autocorrelation is found to hold in twelve of the fifteen countries, suggesting that the original finding has relevance to countries besides America. And although the results from this study do not persistently reject the random-walk hypothesis across timeframes and countries, they do provide strong evidence that there is negative autocorrelation in long-term returns.

Fama and French (1988a) expand on Poterba and Summers' study by analysing the portion of long-term return variance explained by negative long-term return autocorrelation. Using industrial portfolios constructed from stocks listed on the New York Stock between 1926 and 1985 and regression analysis, they find that roughly 35% of return variance can be explained by negative return autocorrelation.

Thus, the literature provides strong evidence of a long-term mean reversion effect in the prices of markets.

3.2.3 Additional Predictors of Market Returns

The above literature focuses on return serial dependence or independence. However, future returns may be dependent on factors apart from their history. According to Gordon's dividend discount model, factors such as the retention ratio, dividend and earnings yield and earnings growth provide an indication of the required rate of return for an investment. The below provides an overview of these additional factors and how they impact future returns.

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Jaffe & Mandelkar (1976) provide an early example of using other determinants to forecast the market. In a study which purpose is to test whether an equally weighted portfolio of stocks on the NYSE between 1953 and 1971 act as inflation hedge, they find, using regression analysis, that both real and nominal one-month returns have a significant negative relationship with historic monthly inflation. However, the variance of returns explained by lagged inflation is limited between 2.7 and 4.9%, depending on specification, suggesting that a trading strategy developed from this relationship will not be extremely successful. The results of this finding are confirmed by the work of Bodie (1976) and Fama and Schwert (1977).

Campbell (1987) tests whether future excess returns on a value-weighted NYSE index are dependent on one-month, two-month less one-month, six-month less one-month and a one period lag of six-month less one-month US Treasury bills. Using OLS regression estimations for two sample periods, 1959-1979 and 1980-1983, he finds that a combination of term-structure of interest rate variables acts as a significant forecaster of excess returns.

Fama and French (1988a) study the predictive power of dividend yields on market returns. Testing this theory on monthly, quarterly and one, two, three and four year returns of two market portfolios on the NYSE for the period 1927-1986, they find that dividend yields explain less than 5% of the variance of quarterly or monthly returns, but in excess of 25% for yearly or longer returns.

Campbell and Shiller (1998) use dividend yield and a 10-year earnings smoothed price/earnings ratio as a predictor of price growth on the S&P 500 from 1872. They find that dividend yield is positively correlated and price/earnings negatively correlated with 10-year S&P 500 price growth, with dividend yield explaining 15% of variance and the smoothed price/earnings ratio 37% of variance. They expand their study by analysing scatter plots of dividend yield and future price growth internationally, and find visible positive relationships in Australia, Canada, the United Kingdom, Netherlands, Spain, Sweden, Switzerland and Japan and no visibly observable relationship in France, Germany and Italy. Campbell and Yogo (2006) further test this relationship using monthly, quarterly and annual returns on a value-weighted portfolio of the NYSE/AMEX from 1926 to 2002. Using an adjusted Bonferroni test, they find that the smoothed price/earnings ratio is a significant predictor of monthly, quarterly and annual returns, while dividend yield is a significant predictor of annual returns.

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Fama and French (1989) combine the predictive nature of dividend yield and the term spread, as well as the default spread. Defining the term spread as the difference between the yield on the Aaa bond portfolio and the one-month treasury bill rate and the default premium as the difference between the portfolio of corporate bonds and the Aaa bond portfolio, and using both a value and equally weighted index of stocks on the NYSE between 1927 and 1987, they generate two OLS multifactor regressions (dividend yield and term spread; default premium and term spread) to analyse the portion of market returns that are predictable. For short-term returns (1-month and quarterly returns), they find little predictive power. However, for long-term returns (1-4 year returns), there is stronger evidence of predictive power. A combination of dividend yield and the term spread explains 25% and 34% of the variability of four-year returns on the value and equally-weighted NYSE index respectively, while a combination of the default spread and the term spread explains 13% and 23% of the variability of four-year returns on the value and equally-weighted NYSE index respectively. Limiting the sample to returns from 1941 to 1987 increases the predictability of returns, with a combination of dividend yield and the term spread predicting 60% of the variability of four-year returns on the value-weighted NYSE index.

In an additional line of research, Balvers, Cosimano and McDonald (1990) develop and test a general equilibrium model examining the potential of rationally developed expectations of output growth to forecast returns. Empirically, this is simplified to test whether stock returns are predictable using aggregate output. Using the value-weighted index of the NYSE, for share returns, and data on industrial production, for aggregate output, from 1947-1987, they find, using OLS regression estimation, that roughly 20% of variance in future real annual returns can be explained by current output. They then test the same relationship with monthly and quarterly data, finding the predictive component dropping to 3% and 8% respectively, and 5-year returns, where the predictive component increases to 50%. They then expand their study to include quarterly data in Canada and the United Kingdom, and find that the predictive component in these countries remains roughly in line with that of the United States.

Ferson and Harvey (1993) analyse the predictability of excess US dollar monthly returns of MSCI indices for 18 countries for the period 1970 to 1989. Their predictive variables can be summarised into three groups: risk premiums from a beta pricing model of the most important risk factors from the dollar returns of the MSCI

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World Index, value weighted currencies of 10 industrialised countries, unexpected value-weighted inflation in the G7 nations, monthly changes in inflation expectations in the G7 nations, the premium on Eurodollars treasury rates over US Treasury rates, the weighted average of short-term rates in the G-7 nations, the monthly change in dollar oil prices, and the weighted average of the industrial growth in the G-7 nations; global predetermined variables consisting of the one-month Treasury bill yield, the dividend yield of the MSCI World Index, the term spread of long and short-term US Treasury bills, the spread between US and Eurodollar Treasury bills, lagged returns of the MSCI World Index and a dummy variable for the month of January; and country specific variables consisting of the short-term interest yield of the local country, the term spread between long and short-term bond yields, and the lagged returns of the local stock index. The predicted variability explained by these variables of the local index (using R^2 as the measure of predicted variability) ranges from 5.6% of returns in the Swedish index to 20.2% of returns in the US Index.

3.2.4 Trading Strategies based on Forecast models

The above literature provides evidence that the variability of market returns can be partially explained through the use of certain historic variables. However, practically, the ability of a variable to predict returns is ineffectual if it cannot be used in a trading strategy that outperforms a passive index. Breen, Glosten and Jagannathan (1989), in one of the earliest studies of its kind, utilise Treasury bill returns to develop a forecast model of excess returns of the value weighted index of NYSE stocks, and then utilise these forecasts to develop a trading strategy between April 1954 to December 1986. Their forecast model is generated using 36-months' worth of previous data to forecast one month forward and their trading strategy assumes that their hypothetical investor is invested fully in stocks (bonds) when the forecast of excess returns is positive (negative). Finding a statistically significant negative correlation between Treasury bill rates and future excess returns, they then determine that the excess performance generated by utilising these forecasts for the value-weighted index is equivalent to 2% of the portfolio.

In a simplistic, earnings based strategy, Downe, O'Connor, Shapiro and Reid (2004) use the 10 year moving average of accounting returns for the Standard & Poor's 500 (S&P 500) to calculate price smoothed earnings ratios. They then use a rolling window regression technique to forecast actual returns based on the price-

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smoothed earnings ratios. They defined the equity risk premium as the forecast return minus the current yield on a 10-year government bond. It is assumed that the value of the investment is fully invested in bonds when the risk premium was negative or zero and fully invested in shares when the risk premium was positive. For the period from 1953 to 2002, their method gave a better return than the benchmark S&P 500 index, but the improvement was only marginal (less than 1% per year).

Andersen (1996) develops a forecast model of six-month S&P 500 excess returns for 1964 to 1993 using five variables: dividend yield; the year-on-year change in consumer inflation; the year-on-year change on the spread between Baa and Aaa corporate bond yields; historic two-year returns on the S&P 500; and the difference between US excess reserve and borrowing of depository institutions. Using OLS regression analysis, he finds that 41% of variance in excess returns can be predicted using these variables over the entire sample. He then uses a rolling regression within the sample to generate a forecast for one-period ahead of the subsample, transforms this forecast into a probability value and assumes that the hypothetical investor invests this probability in the index with the remainder in a risk-free asset. He finds that the portfolio generated from the forecast model underperforms the S&P 500 by 70 basis points in the period from 1984 to 1993.

In a South African based study, Keuler and Kriger (2009) analyse the potential of an array of variables to develop models that have economically exploitable forecasts that would provide an opportunity for an investor to outperform the Johannesburg Stock Exchange All Share Index between 1986 and 2006. These variables included local measures of inflation, exchange rates, gold and oil prices, short-term risk-free rate, dividend and earnings yields, historic JSE monthly price changes; and international measures of long and short-term risk-free rates and price changes, earnings yields and dividend yields on the S&P 500. Using four different combinations of variables and trends, along with 64 different trading rules to determine when to switch from the JSE ALSI to the risk-free asset and vice versa, Keuler and Krige find that their best combinations, on average, outperforms the JSE ALSI by between 7 and 9% per annum during the sample period assuming zero transaction costs, and 4-5% when this assumption is relaxed. However, with so many potential combinations, there is the possibility of data snooping influencing the results.

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However, numerous studies suffer from a look-ahead bias, as the correlation to determine which variables are significant uses the entire sample's data. It is highly possible that the correlations do not remain constant through time and therefore, the model specification may be wholly different using a limited sample (Pesaran & Timmermann, 1995). To overcome this bias, Pesaran and Timmermann (1995) suggest that all combinations of relationships between potential predictive variables and future returns should be estimated at point t within the sample. The model with the best goodness-of-fit is then selected and used to generate a forecast of the next periods return. This is then repeated for the following period, until the full sample has been evaluated.

Their work focuses on the ability of dividend and earnings yield, short and long-term Treasury bill rates, inflation and changes in industrial output and money supply, to predict future excess monthly returns on the S&P 500 from December 1959 to November 1992. They also test the economic impact of the selection of goodness-of-fit statistic. In the majority of hypothetical portfolios with different assumed transaction costs, they find that trading strategies based on recursively estimated forecast models can provide average returns in excess of the S&P 500 with substantially lower standard deviations. Pesaran and Timmermann (2000) expand and extend this methodology to the United Kingdom, with similar results.

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The literature above shows that, after an initial stage where returns are thought to be unpredictable, a belief began to grow that a certain portion of the market is predictable. With this finding becoming growingly entrenched, research began on the ability to exploit the forecasts and generate returns in excess of the market through the use of market timing or asset allocation. The results are ambiguous, with some research finding evidence of potential outperformance and others not. Outperformance is also highly reliant on the specification of the model, with differences in selection criteria, training period and trading strategy leading to wholly different results.

4 Data and Methodology

The aim of this chapter is to provide a broad overview of the data and methodology that is used in this study. In chapter 4.1, the data chosen for this analysis is described, while chapter 4.2 details the methods applied within this study.

4.1 Data

As this study attempts to forecast the JSE All Share Index throughout time, it is imperative that the dataset includes as many observations possible. Due to data limitations of potential explanatory variables which have been shown to have significant forecasting power (such as earnings yield), the earliest monthly data available from the I-Net Bridge database only exists from January 1960. Given that the model was built during the course of 2010, the sample ends at the end of January 2010, and, as such, there are a maximum of 601 monthly observations available for use for this study.

As discussed in the overview of empirical literature, it has been found that the inferences that are drawn forecasting short-term returns instead of long-term returns can be vastly different. As such, this study will produce results for both long and short-term return timeframes by analysing the return predictability of one, three, six, twelve and twenty-four month returns. As the returns obtained from I-Net Bridge database do not include dividends, the relevant time-period adjusted dividend yield is added to the relevant return to provide a proxy of the total return of the JSE ALSI. This adjusted dividend yield is calculated as $\overline{DY}_t = DY_t \frac{m}{12}$, where m is the length of the return timeframe, replicating that of Firer and McLeod (1999) who found this method, while not generating perfectly correct total returns, approximates the correct returns in such a manner that the difference between the actual returns and the approximate returns is materially negligible, due to the fact that price behaviour dominates the variation in index returns.

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In attempting to forecast market returns, the next question is simple: what variables could be accurate forecasters of future returns? There is a trade-off involved in this: certain variables only have available data at a later stage. Thus, the extra predictive capability that these variables might add is countered by the decrease in sample size, and therefore, significance of inferences that can be drawn from any results generated by the model.

To maximise the length of the sample size, only variables available from 1970 or earlier are chosen. Each selected variable is chosen based on an overview of the available literature as well as other potential variables that the author might feel relevant. All data was collected from the I-Net Bridge database. These variables, and the method in which they were calculated, are provided below.

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Table 4.1 Summary of Potential Variables

Variable	Definition
Earnings Yield	12-Month Earnings per Share (EPS) / Price
Long-Term Gilt Adjusted Earnings Yield	Earnings Yield / 10-Year Gilt Rate
90-Day Bankers' Discount Rate Adjusted Earnings Yield	Earnings Yield / 90-Day Bankers' Discount Rate
Dividend Yield	12-Month Dividends per Share (DPS) / Price
Long-Term Gilt Adjusted Dividend Yield	Dividend Yield / 10-Year Gilt Rate
90-Day Bankers' Discount Rate Adjusted Dividend Yield	Dividend Yield / 90-Day Bankers' Discount Rate
T-Period Earnings Growth	$\ln(EPS_t) - \ln(EPS_{t-T})$
Term Spread	Long-Term Gilt Rate – Short-Term Risk-Free Asset Rate
Long-Term Gilt Rate	10-Year Gilt Rate (RLRS)
Short-Term Risk-Free Asset Rate	90-Day Bankers' Discount Rate (RBAS)
T-Period Historic Return	$\ln(Price_t) - \ln(Price_{t-T})$
T-Period Overbought/Sold Indicator	($Price_t$ – T-Period Price Moving Average)/(T-Period Price Moving Average) *
Deviation from T-period P/E Moving Average	P/E** – T-Period P/E Moving Average)
Percentage Deviation from T-period P/E Moving Average	(P/E – T-Period P/E Moving Average) / T-Period P/E Moving Average

* Where T-Period Moving Average = $\frac{\sum_{i=0}^{T-1} P_{t-i}}{T}$

** Where P/E = 1/Earnings Yield

Earnings and dividend yields have a theoretical relationship with the rate of return, as derived from Gordon's dividend discount model (1959), such that $r = \frac{D_0(1+g)}{P_0} + g$, where D_0 is dividend received at the current point in time, P_0 is the price of the asset and g is the time-constant growth rate in earnings. Empirical work by Campbell and Shiller (1998) also show that dividends and earnings relative to market prices have some ability to

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forecast movements in a market, with the dividend yield having a positive relationship with future returns and the price/earnings ratio having a negative relationship with future returns. However, this study chooses 1-year earnings yield (as chosen by Pesaran & Timmermann, 1995) as a proxy of relative earnings value, rather than the 10-year earnings smoothed price/earnings ratio chosen by Campbell & Shiller (1998). Adjusted earnings and dividend yields are considered as, in theory, earnings are the driver of returns, and dividends a function of earnings, high dividend and earnings yields indicate the 'cheapness' of the market. Thus, by dividing these yields by proxies of the long and short-term risk-free yields, the adjusted yields provide an indication of the 'cheapness' of the market relative to a risk-free asset. It is therefore expected that when these ratios are high, future stock returns should be high, and vice versa.

The second component of returns in Gordon's dividend discount model is earnings growth and, as such, historic earnings growth, term spread, long-term gilt and 90-days bankers' discount rate, are used to proxy this. One would expect that, if earnings growth has been high historically, investors could feel that this implies growth prospects in the future, and vice versa. Earnings growth itself can be vastly different dependent on the timeframe chosen and to measure these variations, 6, 12, 18, 24, 36 and 48-month timeframes are included in this study. The term-structure of interest rates provide an indication of the expected rate of growth in the economy and are found by Campbell (1987) to have significant forecasting ability of returns, hence the inclusion of interest rate variables in this study. Therefore higher interest rates and a higher term spread indicate higher expected inflation. Higher expected inflation could imply that the economy is growing rapidly, causing increases in the value of goods or services sold, which would then lead into higher earnings growth in the future. However, higher interest rates increase the rate of capital, which could lead to firms embarking on fewer projects, leading to a decline in future earnings.

The remaining variables are indicators of momentum. Historic returns are a direct indicator of past performance, the overbought/sold indicator is a common technical indicator of the value of the market relative to its historic t-period performance and is similar to the momentum variable used in Keuler and Krige (2009), and the two price/earnings variables provide an indication of the relative value of the market relative to its t-period mean. Based on the study by Poterba & Summers (1988), one would expect, in the short-term, these momentum

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variables to accurately forecast a continued movement in that direction while, in the long-term, one would expect there to be a correction and the direction of price movements to change. Like earnings growth, different time frames can lead to vastly different values for these momentum variables and, like earnings growth, more than one timeframe is chosen to account for this. Thus, for historic returns, 1, 3, 6, 12, 18, 24, 36, 48 and 60-month timeframes are included; for the overbought/sold indicator, 3, 4, 5, 6 month and 1, 2, 3, 5 and 10 year timeframes are included; and for deviations and percentage difference from P/E moving average, 3, 5 and 10-year timeframes are included.

4.2 Methodology

With the numerous variations on certain indicators, there are a total of 39 potential variables included for analysis in this study. An initial descriptive analysis of the means and standard deviations of the variables is followed by a correlation analysis between the dependent variables and each independent variable, lagged by the relevant time period, such that $r = \frac{\sum_{t=1}^{n}\left(Y_t - \overline{Y}\right)\left(X_{t-T} - \overline{X}\right)}{\sqrt{\sum_{i=1}^{n}\left(Y_t - \overline{Y}\right)^2}\sqrt{\sum_{i=1}^{n}\left(X_{t-T} - \overline{X}\right)^2}}$, where Y is the dependent return, X is the independent variable being tested, n is the number of observations in the sample, and T is the length of the return forecast. To determine suitability, the correlations are tested, by transforming the correlations using the method suggested by Fisher (1915), such that the correlation is normally distributed with mean $\frac{1}{2}\ln\left(\frac{1+r}{1-r}\right)$ and standard error of $\frac{1}{\sqrt{n-3}}$, where r is the correlation between variables and n is the sample size, against a null hypothesis of a correlation of zero, using a traditional z-test. Variables that are significantly correlated, at the 10% level, are then selected for further analysis, thereby reducing the large number of potential variables to only include those that display significant forecasting ability. In the case where two or more similar variables are significant at the 10% level, the variable with the highest correlation is chosen, thereby excluding the other variable or variables. This is done to avoid excessive multicollinearity.

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At this stage, the suitability of each candidate variable to enter a more thorough analysis is tested. An initial visual analysis, comparing the variable with the ALSI over the sample period, is undertaken, to ensure that there are potential relationships and that there are no clear trends in the variables that may suggest non-stationarity. A more rigorous test for a unit-root, the Augmented Dickey-Fuller test, is then undertaken on the dependent and candidate independent variables. Any variable that has a unit root is excluded from the study.

Two subsamples, ranging from 1960-1985 and 1985-2010, are analysed independently to determine whether there is a mid-sample structural breaks. A rudimentary analysis, by comparing the means of the variables within the two subsamples, is followed by a comparison of the correlations in the two subsamples. Finally, a more statistically rigorous approach is used to test for a structural break, through a single-factor regression analysis over the entire period that includes subsample dummy coefficients, such that $Y_t = \beta_0 + \beta_1\left(D_{t-T}\right) + \beta_2\left(X_{t-T}\right) + \beta_3\left(X_{t-T}.D_{t-T}\right)$, where Y is the relevant return timeframe, D is a dummy variable indicating whether the observation is within the second subsample, X is the relevant independent variable and T is the length of the return horizon that is being tested.

Finally, the correlations of the independent variables are analysed for potential multicollinearity. As multicollinearity does not impact on the predictive power of the model, only variables with a correlation with another independent variable in excess of 0.95 are removed.

With the candidate variables chosen and those that fail tests of statistical suitability removed, a possible cointegrating relationship between certain value variables and the JSE is estimated. Four variables are chosen: the market capitalisation weighted average of earnings per share, the 90-Day Bankers Discount Rate, the Rand/US$ exchange rate and the Economist Metal Index. Earnings per share is included as, in theory, earnings are the primary driver of market prices. The 90-Day Bankers Discount Rate is chosen as it provides a measure of short-term inflation and therefore an indicator of both the cost of borrowing and inflation expectations. The Rand/US$ exchange rate and the Economist Metal Index are included due to the resource dependent nature of the JSE ALSI. When commodities increase in value, thereby causing the Economist Metal Index to increase in value, one could expect that future expectations of earnings on the JSE ALSI will also rise, and vice versa. When

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the Rand depreciates, the Rand value of resources shares will increase, leading to greater earnings and possible increases in expected future earnings, and vice versa. Therefore both variables should provide indications as to the long-term fundamental value of the JSE ALSI. The relationship is specified as $ALSI_t = \beta_0 + \beta_1 EPS_t + \beta_2 RBAS_t + \beta_3 US\$/R_t + \beta_4 \text{Economist Metal Index}_t + \varepsilon_t$. This relationship is determined using the Engle & Granger methodology. The residual is tested to determine whether an error-correcting mechanism exists by estimating $\Delta y_t = \beta_0 + \sum_{i=1}^{k} B_i \Delta x_{i,t} + \delta z_{t-1} + u_t$, where y is the dependent variable (in this case, the JSE ALSI), k are the number of independent variables in the long-run relationship, x_i is the i^{th} explanatory variables and z is the error term from the long-run relationship (Gujarati, 2003). If the coefficient on the residual of the long-run relationship is negative and statistically significant, it satisfies the conditions and one can infer that there is an error-correcting mechanism. If there is an error-correcting mechanism, the residual is then tested, through a correlation analysis between the residual and the dependent variables, with a significance level of 10%, to determine whether it is fit for inclusion in the predictive forecast model.

As an OLS regression is a simple and common method for creating a forecast model, it is used in this study, specified as $Y_t = \beta_0 + \sum_{i=1}^{n} \beta_i X_{i,t-T} + \varphi_i X_{i,t-T}.D_{i,t-T} + \varepsilon_t$, where Y is the return on the ALSI for the relevant timeframe, n is the number of variables chosen for the analysis, X is an independent variable, D is a dummy variable for a structural break and T is the forecast horizon length. If no mid-sample break is found in the earlier analysis, the associated dummy coefficient is set to zero.

To more thoroughly check the goodness-of-fit of the model, over and above the value of R^2, the forecasts are regressed against the actual returns to determine whether there are any forecast biases. The intercept and slope coefficient are tested to determine whether they are significantly, at the 10% level, different from an intercept and slope coefficient of zero and one respectively. If there is a significant difference, the forecasts will systematically over or under-estimate the forecasted return.

Although this analysis indicates how accurately the forecast model can forecast the actual return, there is also value in a model that can accurately predict the direction of the return. Thus, a 'hit-rate' is constructed, calculated

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as the number of times a positive prediction is followed by a positive return and a negative prediction is followed by a negative return as a percentage of the total forecasts made. However, because the JSE trends upwards, a pure buy-and-hold strategy will have a hit-rate in excess of 50%. One method to account for this, as suggested by Bodie, Kane and Marcus (2008) is to decompose the excess forecasting ability into bull and bear periods, such that $P = P_{BULL} + P_{BEAR} - 1$, where P is the proportion of correct forecasts within the relevant period. However, the methodology, by construction, equally weights success in bull and bear markets. With long-term returns, where positive returns are highly frequent, this will bias the forecast success rate towards the bear period performance (i.e. it will overstate predictive power if forecasts are more successful in bear periods and vice versa). As such, a less elegant, simplistic comparison of the forecasts' hit-rate relative to the hit-rate of a pure buy-and-hold strategy over the sample period is utilised.

The forecasts from the five models are then transformed into the forecast probability of the JSE ALSI outperforming the risk-free asset by assuming that the return prediction follows a normal distribution with standard error equal to the standard error of the regression. This forecast probability is then used to implement three hypothetical trading strategies, which allocates an investment between two asset classes, the JSE ALSI and the risk-free asset (using the RBAS as a proxy), based on the trading strategies created by Andersen (1996).

The first strategy invests 100% in the JSE ALSI when it exceeds a cut-off level, otherwise investing 100% in the risk-free asset. As this is quite a risky strategy, especially if the probability value is near the cut-off, the second strategy invests a portion in the JSE ALSI and a portion in the risk-free asset, with each portion dependent on the value of the probability of outperformance. The final strategy takes into account the profits that can be generated if a short position is taken in the JSE ALSI when the investor believes there will be a decline in value. The results of these trading strategies are then compared to the returns that would have been generated by a pure buy-and-hold strategy in the JSE ALSI. The formulations of the three strategies are summarised in the table below.

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Table 4.2 Summary of Trading Strategies

	Trading Strategy A	Trading Strategy B	Trading Strategy C
JSE ALSI	100% if p > z; 0% if p <= z	p%	(2p – 100)%
RBAS	0% if p > z; 100% if p <= z	(100-p)%	(200 – 2p)%

P is the forecasted probability that the JSE ALSI will yield a positive return over the relevant holding period.

However, it is possible that longer-term forecasts may have greater predictive power than short-term returns. If this assumption holds, the additional information content in longer-term forecasts can be transferred to shorter-term forecasts through implicit forecasts, defined as $\overline{Y}_{t,t+T} = E\left[Y_{t-Z+T,t+T} \mid X_{t-Z+T}\right] - R_{t-Z+T,t}$; $Z > T > 0$, where $\overline{Y}_{t,t+T}$ is the forecasted return on the market from period t to period t+T, $R_{t-Z+T,t}$ is the actual return realised from period t-Z+T to period t, T is the length of the short-term forecast, Z is the length of the long-term forecast, and X_i is a vector of variables, at time t-Z+T, used to generate the long-term forecast. If the longer-term forecast provides additional explanatory power, the coefficient on its implicit forecast in a shorter-term forecast regression will be significantly different from zero; otherwise it will not be significantly different from zero and its inclusion should have a negligible effect on the regression estimation and results.

All available implicit forecasts are added to 1, 3, 6 and 12-month return horizons (as 24-month is the longest-term return forecast, no implicit forecasts can be generated), with the forecasts undergoing the same goodness-of-fit tests, transformations and implementation in the same three trading strategies. The returns are then compared to both a pure buy-and-hold strategy in the JSE ALSI, as well as the returns generated from the initial forecast model.

However, both forms of model suffer from significant look-ahead bias, as the variables are chosen and coefficients estimated on the entire sample of data. It is improbable that the coefficients and the correlations between potential independent variables and dependent returns remain constant. Therefore a model generated in, for example, 1980, using only data that is historically available, may lead to a model that has different coefficients or, more worryingly from the perspective of relevancy, a model specified with different variables, relative to the model generated with the full sample of data. As the purpose of this study is to proxy a manager

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quantitatively converting publically available data into forecasts of market movements, this look-ahead bias needs to be avoided.

To limit this shortcoming, a dynamically updating out-of-sample model is generated, following a method similar to Pesaran & Timmermann (1995). At each point in time, the 39 additional variables, as well as the cointegrating relationship, are created. At this stage, Pesaran & Timmermann (1995) estimated models that take into account every single possibility of variable selection, and, using a goodness-of-fit statistic, chose the best model to utilise for the prediction generation process. However, this study chooses to use a correlation analysis, as used in the in-sample analysis above, including variables that are statistically significant at the 10% level are then used in a regression analysis. However, where two or more variables that are similar are significant at the 10% level, the most significant is chosen. Both methods have their merits but model selection based on Pesaran & Timmermann's (1995) goodness-of-fit methodology would require the generation of thousands of models per month. The generation of this many models is computationally intense today and it is most certainly improbable that an investor in the 1970s or 1980s would be able to replicate the methodology. As the purpose of this study is to simulate a manager's ability to transform raw publically available data into useful forecasts, the more complex goodness-of-fit methodology has to be rejected, based on this improbability, and the simpler correlation analysis is chosen. The cointegrating relationship is assumed to remain constant through time, although the residual from this relationship is only included if the correlation between it and the relevant dependent variable is statistically significant at the 10% level. With the initial models selected, OLS regressions between the candidate variables and the relevant depend returns are estimated to generate the initial models. The longer-term initial models are transformed into implicit forecasts, as above, and included in the specification for the relevant short-term models, which are re-estimated to generate the augmented model.

However, the choice of training period for the dynamically updating model can lead to significantly different results. To prevent the results of this study to be dependent on an arbitrarily selected training period, the methodology is repeated for a 5, 7 and 10-year rolling regression, as well as a 10-year expanding horizon regression, where an initial sample of 10-years is then expanded with the addition of new observations as they become available.

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These forecasts are then transformed into probabilities assuming, as above, that the forecasts follow a normal distribution with a standard error equal to the standard error of the regression at time t. These probabilities of outperformance are then applied to the three hypothetical trading strategies. The results of these returns are then compared to a pure buy-and-hold strategy, the returns generated from the in-sample forecast models generated earlier, as well as the returns generated by other dynamically updated models with different training periods.

Throughout the study, taxation is ignored. Transaction costs are also initially ignored, although this assumption is relaxed later in this study.

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5 Descriptive Statistics and Exploratory Analysis

This chapter presents the exploratory statistical results yielded from this study. The chapter is organised as follows. Section 5.1 presents the descriptive statistics of all variables as well as an analysis of the correlations between independent variables and various future return timeframes to choose candidate variables that show significant predictive power. Section 5.2 then analyses the candidate variables to ensure they are fit for inclusion in the later multifactor forecast models. Section 5.3 develops and tests a cointegrating relationship on the JSE, so as to create a variable that will forecast movements back to an assumed fundamental value.

5.1 Descriptive Statistics

The initial step when attempting this statistical research is to examine the descriptive statistics of all variables that are being considered. This section is broken up into various subsections. 5.1.1 analyses the means and standard deviations of both dependent and independent variables, thus providing the starting point of the research. 5.1.2 then provides the correlations between the five dependent variables and the lagged independent variables, to provide a cursory overview of the predictive strengths of any possible relationships between dependent and an independent variable, concluding with a list of candidate independent variables suitable for inclusion in each return timeframe's multifactor forecast model.

5.1.1 Means and Standard Deviations of Variables

The table below presents the means and standard deviations of the sample of potential predictor variables, beginning with earnings and dividend yield related variables, including adjustments for long-term interest rates, using the long-term gilt (abbreviated as RLRS) as a proxy, and short-term interest rates, using the 90-Day Bankers Discount Rate (abbreviated as RBAS) as a proxy, followed by earnings growth variables, interest rate related variables, overbought/sold indicator variables, historic return variables, and finally, price/earnings variables, in that order, for the period January 1960 – January 2010.

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Table 5.1 Means and Standard Deviations of Variables (January 1960 – January 2010)

Variable	Mean	Standard Deviation	Variable	Mean	Standard Deviation
Valuation Variables					
Earnings Yield	0.0953	0.0350	Dividend Yield	0.0451	0.0192
RLRS Adjusted Earnings Yield	0.8916	0.3888	RLRS Adjusted Dividend Yield	0.4184	0.2209
RBAS Adjusted Earnings Yield	1.0362	0.5657	RBAS Adjusted Dividend Yield	0.4888	0.3026
Growth Variables – Earnings Growth					
6 Month Earnings Growth	0.0551	0.0786	24 Month Earnings Growth	0.2300	0.2127
12 Month Earnings Growth	0.1127	0.1295	36 Month Earnings Growth	0.3496	0.2620
18 Month Earnings Growth	0.1713	0.1737	48 Month Earnings Growth	0.4662	0.2792
Growth Variables – Interest Rates					
Term Spread	0.0089	0.0246	90-Day Bankers' Discount Rate	0.1063	0.0434
			Long-Term Gilt	0.1152	0.0359

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Table 5.1 Means and Standard Deviations of Variables (January 1960 – January 2010)

Momentum Variables – Overbought/Sold Indicators					
3 Month Overbought/Sold	0.0100	0.0484	1 Year Overbought/Sold	0.0595	0.1280
4 Month Overbought/Sold	0.0154	0.0617	2 Year Overbought/Sold	0.1291	0.1948
5 Month Overbought/Sold	0.0210	0.0731	3 Year Overbought/Sold	0.2004	0.2429
6 Month Overbought/Sold	0.0265	0.0833	5 Year Overbought/Sold	0.3436	0.3080
			10 Year Overbought/Sold	0.7344	0.4566
Momentum Variables – Historic Returns					
1 Month ALSI Return	0.0133	0.0625	24 Month ALSI Return	0.3335	0.3043
3 Month ALSI Return	0.0405	0.1153	36 Month ALSI Return	0.5061	0.3352
6 Month ALSI Return	0.0821	0.1650	48 Month ALSI Return	0.6745	0.3490
12 Month ALSI Return	0.1635	0.2266	60 Month ALSI Return	0.8369	0.3522
18 Month ALSI Return	0.2471	0.2766			
Momentum Variables – P/E Variables					
Deviation from 3 Year P/E Moving Average	0.1212	2.5050	Percentage Difference from 3 Year P/E Moving Average	0.0205	0.2089
Deviation from 5 Year P/E Moving Average	0.1664	2.8564	Percentage Difference from 5 Year P/E Moving Average	0.0252	0.2441
Deviation from 10 Year P/E Moving Average	0.0189	3.4121	Percentage Difference from 10 Year P/E Moving Average	0.0220	0.3043

Sample Period: 1 January 1960 – 31 January 2010. Earnings Yield is measured as EPS/P. Dividend Yield is measured as DPS/P. RLRS Adjusted Earnings Yield is measured as Earnings Yield/RLRS. RLRS Adjusted Dividend Yield is measured as Dividend Yield/RLRS. RBAS Adjusted Earnings Yield is measured as Earnings Yield/RBAS. RBAS Adjusted Dividend Yield is measured as Dividend Yield/RBAS. T-Month Earnings Growth is measured as ln(EPS(t))-ln(EPS(t-T)). Term Spread is calculated as RLRS – RBAS. % Overbought/Sold Indicator is measured as $(P_t\text{-}MA_t)/MA_t$. T-period historic returns are calculated as $\ln(ALSI_t)\text{-}\ln(ALSI_{t\text{-}T})$. Deviation from P/E moving average is calculated as $(PE_t\text{-}MA_t)$. % difference from moving average P/E is calculated as $(PE_t\text{-}MA_t)/(MA_t)$.

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As expected, the means of earnings and dividend yields are positive. Their standard deviations are relatively small compared to the means, indicating that these yields are almost always positive; an expected result as market capitalisation-weighted earnings are rarely negative, and dividends are always non-negative. The mean of the earnings yield is slightly more than double the mean of the dividend yield, suggesting that, on average, the market pays out less than 50% of its earnings in the form of dividends. However, the standard deviation of the dividend yield is smaller than that of the earnings yield, which suggests that there is dividend stability, although the standard deviation must be taken in the context of its relatively smaller mean.

The mean of the RLRS adjusted earnings yield is slightly below 1, which indicates that, on average, the earnings yield, providing a measure of the intrinsic return on the market, is less than the return offered by the long-term gilt. However, the mean is less than one standard deviation from 1, indicating that it is highly possible for the earnings yield to be greater than the long-term gilt at any point in time. The mean of the RBAS adjusted earnings yield is marginally over 1, but there is almost an equal probability of earnings yield being greater than or less than short-term bond returns. The standard deviation of the RLRS adjusted earnings yield is substantially lower than the RBAS adjusted earnings yield, suggesting that short-term bond returns are more volatile than long-term rates; another expected result.

The adjusted dividend yield follows a similar pattern. The mean of the RBAS adjusted dividend yield is marginally higher than the mean of the RLRS adjusted dividend yield, with the standard deviations of the RBAS adjusted dividend yield higher than that of the RLRS adjusted dividend yield. The means are again slightly less than half than the means of the adjusted earnings yield; another expected result as this pattern occurs with their unadjusted yields. The standard deviations of adjusted dividend yields are smaller than those of the respective adjusted earnings yield, which again is expected due to comparatively more stable nature of dividends.

The means of all the earnings growth measures are positive, regardless of timeframe, indicating that earnings tend to increase through time. However, up to and including 18-month earnings growth, the mean is slightly smaller than the standard deviation, which suggests that there is a fairly good possibility that earnings may decline over this time-period. For longer-term earnings growth, the standard deviations are smaller than the means, including significantly smaller standard deviations for 36 and 48-month earnings growth, indicating that,

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over this time frame, earnings growth is highly likely to be positive. This is an intuitive result when one considers that earnings are measured nominally and therefore inflation should consistently increase them, ceteris paribus, while general cyclical patterns consistent with earnings are smoothed out as the length of the measure exceeds the cycle of growth.

The mean of the term spread is slightly positive, indicating that the long-term gilt yield tend to be slightly higher than that of the short-term yield. However, the mean is only marginally greater than a third of the size of the standard deviation of the term spread, meaning that this finding only tentatively holds, with the probability of short-term bond yields being higher than long-term yields almost as likely as the inverse.

The mean of both interest rate variables are roughly one percent different, with the long-term bond yield slightly greater, at roughly 11.5% per annum, than the short-term yield, at roughly 10.6% per annum, as indicated above by the term spread. Both variables have very low standard deviations, with the long-term gilt having slightly less variance than the short-term yield. However, both standard deviations are significantly lower than the standard deviations of the ALSI. This finding indicates that bonds provide returns at significantly lower risk over the time period relative to the JSE ALSI.

The means of market returns, regardless of time frame, is positive, indicating a positive upward trend in the JSE ALSI. However, the standard deviations of returns, up to 24-month returns, are greater than their respective means, suggesting a great amount of return variance around the mean. The means follow a linear progression; however, from 6 months onwards, the mean of the return is less than that expected from a compounded linear progression of 1-month returns, suggesting that there may be autocorrelation in returns. The standard deviations of returns increases as the time frame increases, but this increase occur at a decreasing rate. To briefly test the presence of autocorrelation, this study assumes that if there is no autocorrelation of returns, then the standard deviations should increase at the square root of the increase of the time frame (i.e. the standard deviation of 3-month returns should equal the square root of 3 multiplied by 1-month standard deviation). However, the standard deviations of returns up to 24-months is greater than this, while the standard deviation of returns greater than 36-months is lower than this relationship forecasts.

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The table and figures below summarises these findings.

Table 5.2 Actual and Expected Means and Standard Deviations of Returns

Timeframe	Actual Mean	Expected Mean	Actual Standard Deviation	Expected Standard Deviation
1 Month	0.0133	0.0133	0.0625	0.0625
3 Month	0.0405	0.0404	0.1153	0.1082
6 Month	0.0821	0.0825	0.1650	0.1530
12 Month	0.1635	0.1718	0.2266	0.2164
18 Month	0.2471	0.2685	0.2766	0.2651
24 Month	0.3335	0.3731	0.3043	0.3061
36 Month	0.5061	0.6090	0.3352	0.3749
48 Month	0.6745	0.8855	0.3490	0.4329
60 Month	0.8369	1.2094	0.3522	0.4840

Sample Period: 1 January 1960 – 31 January 2010. Expected mean is calculated as 1-month mean log return multiplied by the number of months of the respective timeframe. Expected standard deviation is calculated as 1-month standard deviation multiplied by the square root of the number of months of the respective timeframe.

Figure 5.1 Graph of Actual and Expected Means of ALSI Returns

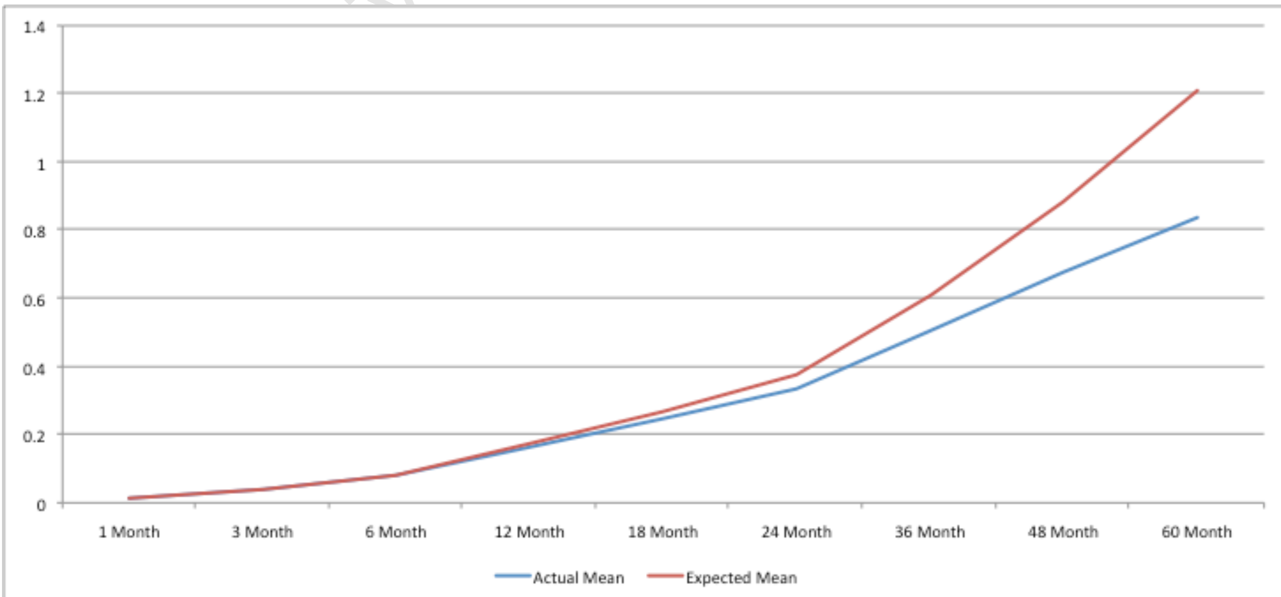

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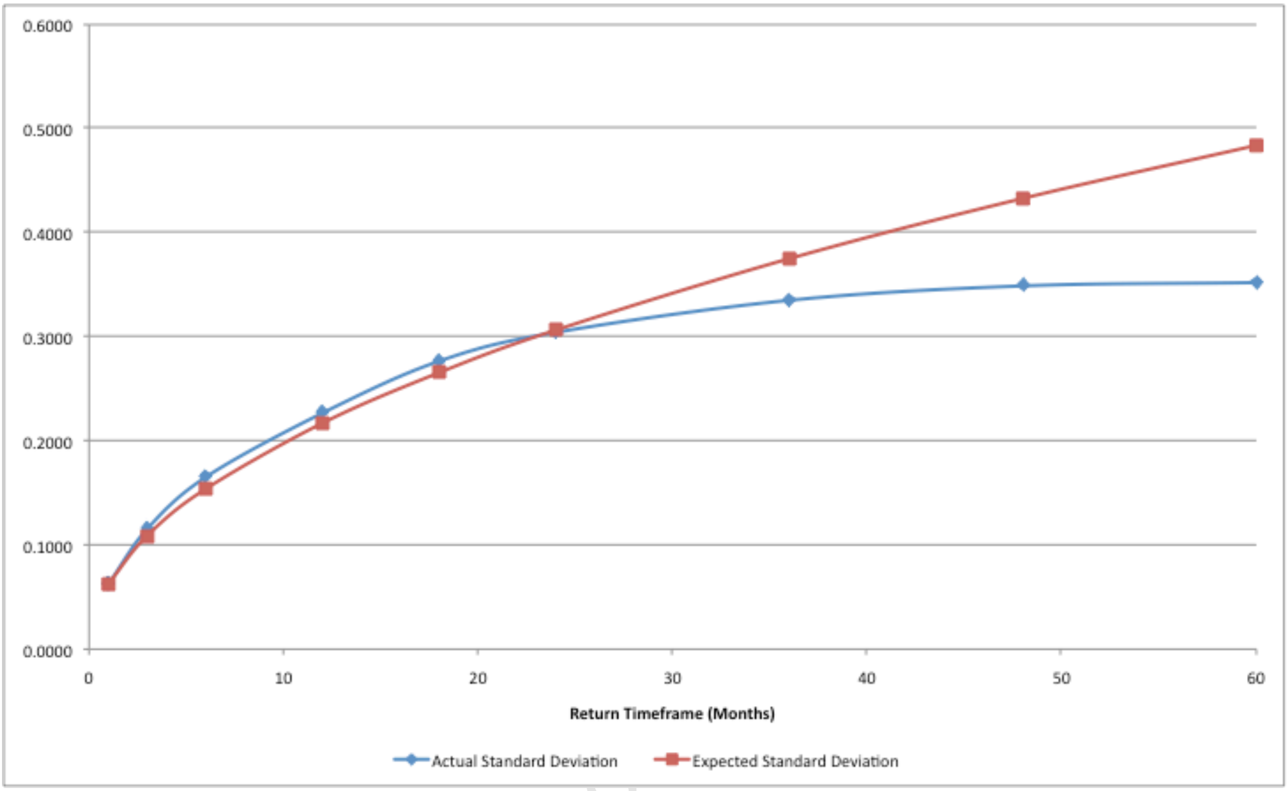
Figure 5.2 Graph of Actual and Expected Standard Deviations of ALSI Returns



The table and figures above suggest that there may be positive autocorrelation in 1-month returns and negative autocorrelation in longer-term returns, as would be expected based on the work of Poterba and Summers (1988). To test this more rigorously, the correlation coefficients between 1, 3, 6, 12 and 24-month returns and the previous return of the same timeframe are generated. Using the Fisher transformation (Fisher, 1915) with a sample of 600, a correlation coefficient of 0.067 would be strong enough to approximately suggest autocorrelation at the 10% significance level (due to the sample sizes of returns variables being less than 600, this approximation is slightly downward biased). These coefficients are shown below, with all correlation coefficients with an absolute value greater than 0.067 bolded.

Table 5.3 Autocorrelation of Return Timeframes

	1 Month	3 Month	6 Month	12 Month	24 Month	36 Month	48 Month	60 Month
Autocorrelation	**0.1028**	0.0456	0.0379	**-0.0759**	**-0.3696**	**-0.4335**	**-0.1484**	**0.0948**

Sample Period: 1 January 1960 – 31 January 2010. Bolded figures exhibit significant autocorrelation at the 10% significance level.

From the table above, there is significant, at the 10% level, positive autocorrelation of 1-month returns through the sample. There is also positive autocorrelation for 3 and 6-month returns, although this is not significant at the 10% level. This explains the greater than expected standard deviations in the short-run. There is then negative and significant, at the 10% level, autocorrelation for timeframes greater than 6-months. This negative autocorrelation increases in strength from 12 to 36-month returns, before declining in strength. This negative autocorrelation in long-term returns therefore explains the lower than expected standard deviations in returns timeframe over 24 months.

The means of all overbought/sold variables are positive, regardless of timeframe, indicating that the market is generally more over-valued (relative to its moving average) than under-valued. However, in the short-run, the standard deviation is proportionately greater than the mean, indicating that this finding only weakly holds. However, the standard deviation becomes proportionately smaller relative to the mean in the longer run, with the standard deviation of the 5-year overbought/sold variable smaller slightly smaller than its mean, and the mean of the 10-year overbought/sold variable almost 1.5 times larger than the standard deviation. This finding indicates that the price of the market is generally much higher than its long-term historic moving average, which suggests that the price of the market follows an upward trend. This finding is again expected, as shares, like all forms of investments, are expected to earn a return to compensate for the time-value of money and risk.

The means of both the absolute and percentage differences of the P/E from its moving average are positive, regardless of the length of the moving average chosen, indicating that the market is generally overvalued relative to earnings. However, the means are relatively small compared to their standard deviation, meaning that the market is almost as likely to be undervalued relative to earnings as it is to be overvalued.

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5.1.2 Correlations between Dependent and Independent Variables

The correlation between an independent variable and a dependent return horizon indicates the predictive power of a return factor with a future return and therefore is the starting basis of developing a multifactor return forecast model. The table below is separated into the various factor types (valuation, growth and momentum), some of which are further broken down due to the varying constructions of different factors. Each correlation of variable with the return is listed with the probability that the correlation is not significantly different from zero, as discussed in the methodology. However, for returns with a return horizon greater than one-month, there will be high serial dependence, as the returns are overlapping (Andersen, 1996). To adjust for this, the number of observations is divided by the timeframe (measured in months) of the return being investigated, such that the standard error is defined as $\frac{1}{\sqrt{n/T-3}}$, where T is the length of the return horizon. As a result of this adjustment, the standard error of the correlation statistic estimates the true standard deviation of a non-overlapping return timeframe, thereby providing an approximate measure of truly independent returns.

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Table 5.4 Correlations between Dependent Returns and Independent Valuation Variables

	Valuation Variables													
	1 Month Returns		3 Month Returns			6 Month Returns			12 Month Returns			24 Month Returns		
	Correlation	P-Value	Correlation	P-Value	Adjusted P-Value	Correlation	P-Value	Adjusted P-Value	Correlation	P-Value	Adjusted P-Value	Correlation	P-Value	Adjusted P-Value
Earnings Yield	**0.0847**	(0.04)	**0.1512**	(0.00)	(0.03)	**0.1982**	(0.00)	(0.05)	**0.2699**	(0.00)	(0.06)	**0.3931**	(0.00)	(0.06)
Dividend Yield	0.0518	(0.20)	0.0962	(0.02)	(0.18)	0.1288	(0.00)	(0.20)	0.1853	(0.00)	(0.20)	0.3005	(0.00)	(0.15)
RLRS Adjusted EY	0.0627	(0.15)	0.1052	(0.01)	(0.16)	0.1340	(0.00)	(0.21)	0.1703	(0.00)	(0.27)	0.2229	(0.00)	(0.33)
RLRS Adjusted DY	0.0353	(0.41)	0.0561	(0.19)	(0.46)	0.0700	(0.11)	(0.52)	0.0956	(0.03)	(0.54)	0.1369	(0.00)	(0.55)
RBAS Adjusted EY	**0.0919**	(0.03)	**0.1333**	(0.00)	(0.07)	0.1565	(0.00)	(0.14)	0.1797	(0.00)	(0.24)	0.1553	(0.00)	(0.50)
RBAS Adjusted DY	0.0626	(0.15)	0.0846	(0.05)	(0.26)	0.0976	(0.02)	(0.36)	0.1121	(0.01)	(0.47)	0.0897	(0.04)	(0.70)

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Table 5.4 Correlations between Dependent Returns and Independent Valuation Variables

	Growth Variables – Earnings Growth													
	1 Month Returns		3 Month Returns			6 Month Returns			12 Month Returns			24 Month Returns		
	Correlation	P-Value	Correlation	P-Value	Adjusted P-Value	Correlation	P-Value	Adjusted P-Value	Correlation	P-Value	Adjusted P-Value	Correlation	P-Value	Adjusted P-Value
6-Month Earnings Growth	0.0417	(0.31)	0.0623	(0.13)	(0.38)	-0.0068	(0.87)	(0.95)	-0.0132	(0.75)	(0.93)	-0.1662	(0.00)	(0.44)
12-Month Earnings Growth	0.0617	(0.14)	0.0517	(0.21)	(0.47)	-0.0148	(0.72)	(0.89)	-0.0961	(0.02)	(0.52)	-0.2858	(0.00)	(0.18)
18-Month Earnings Growth	0.0044	(0.91)	-0.0184	(0.66)	(0.80)	-0.1006	(0.02)	(0.33)	-0.2012	(0.00)	(0.17)	-0.3389	(0.00)	(0.11)
24-Month Earnings Growth	-0.0461	(0.27)	-0.0960	(0.02)	(0.19)	-0.1607	(0.00)	(0.12)	**-0.2628**	(0.00)	(0.07)	**-0.3749**	(0.00)	(0.08)
36-Month Earnings Growth	-0.0562	(0.18)	-0.0945	(0.03)	(0.20)	-0.1662	(0.00)	(0.11)	**-0.2634**	(0.00)	(0.08)	-0.2859	(0.00)	(0.19)
48-Month Earnings Growth	-0.0522	(0.22)	-0.0978	(0.02)	(0.19)	-0.1517	(0.00)	(0.15)	-0.1843	(0.00)	(0.23)	-0.1033	(0.02)	(0.65)

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Table 5.4 Correlations between Dependent Returns and Independent Valuation Variables

	Growth Variables – Interest Rates													
	1 Month Returns		3 Month Returns			6 Month Returns			12 Month Returns			24 Month Returns		
	Correlation	P-Value	Correlation	P-Value	Adjusted P-Value	Correlation	P-Value	Adjusted P-Value	Correlation	P-Value	Adjusted P-Value	Correlation	P-Value	Adjusted P-Value
Long-Term Gilt Rate	0.0126	(0.77)	0.0295	(0.50)	(0.70)	0.0460	(0.29)	(0.67)	0.0943	(0.03)	(0.54)	0.1534	(0.00)	(0.51)
90-Day Bankers Discount Rate	-0.0222	(0.61)	-0.0193	(0.65)	(0.80)	0.0013	(0.98)	(0.99)	0.0472	(0.28)	(0.76)	0.1486	(0.00)	(0.52)
Term Spread	0.0575	(0.18)	0.0770	(0.07)	(0.31)	0.0646	(0.14)	(0.55)	0.0541	(0.21)	(0.73)	-0.0404	(0.36)	(0.86)

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Table 5.4 Correlations between Dependent Returns and Independent Valuation Variables

	Momentum Variables – Overbought/Sold Indicators													
	1 Month Returns		3 Month Returns			6 Month Returns			12 Month Returns			24 Month Returns		
	Correlation	P-Value	Correlation	P-Value	Adjusted P-Value	Correlation	P-Value	Adjusted P-Value	Correlation	P-Value	Adjusted P-Value	Correlation	P-Value	Adjusted P-Value
90-Day Overbought/Sold	**0.0947**	(0.02)	0.0809	(0.05)	(0.26)	-0.0041	(0.92)	(0.97)	0.0414	(0.32)	(0.78)	-0.0590	(0.16)	(0.79)
120-Day Overbought/Sold	**0.0879**	(0.03)	0.0668	(0.10)	(0.35)	-0.0171	(0.68)	(0.87)	0.0313	(0.45)	(0.83)	-0.0767	(0.07)	(0.73)
150-Day Overbought/Sold	**0.0850**	(0.04)	0.0456	(0.27)	(0.52)	-0.0254	(0.54)	(0.80)	0.0190	(0.65)	(0.90)	-0.0912	(0.03)	(0.68)
180-Day Overbought/Sold	**0.0722**	(0.08)	0.0270	(0.51)	(0.71)	-0.0322	(0.43)	(0.75)	0.0100	(0.81)	(0.95)	-0.1039	(0.01)	(0.63)
1-Year Overbought/Sold	0.0374	(0.36)	0.0112	(0.79)	(0.88)	-0.0190	(0.65)	(0.85)	-0.0153	(0.71)	(0.92)	-0.1797	(0.00)	(0.41)
2-Year Overbought/Sold	0.0141	(0.74)	-0.0226	(0.59)	(0.76)	-0.0664	(0.11)	(0.52)	-0.1217	(0.00)	(0.42)	-0.2876	(0.00)	(0.18)
3-Year Overbought/Sold	-0.0141	(0.74)	-0.0647	(0.13)	(0.38)	-0.1222	(0.00)	(0.24)	-0.1984	(0.00)	(0.19)	**-0.3759**	(0.00)	(0.08)
5-Year Overbought/Sold	-0.0497	(0.25)	-0.1217	(0.00)	(0.10)	**-0.2029**	(0.00)	(0.06)	**-0.3054**	(0.00)	(0.04)	**-0.4382**	(0.00)	(0.04)
10-Year Overbought/Sold	-0.0562	(0.22)	-0.1224	(0.01)	(0.12)	**-0.1944**	(0.00)	(0.09)	**-0.2799**	(0.00)	(0.08)	-0.3672	(0.00)	(0.12)

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Table 5.4 Correlations between Dependent Returns and Independent Valuation Variables

	Momentum Variables – Historic Returns													
	1 Month Returns		3 Month Returns			6 Month Returns			12 Month Returns			24 Month Returns		
	Correlation	P-Value	Correlation	P-Value	Adjusted P-Value	Correlation	P-Value	Adjusted P-Value	Correlation	P-Value	Adjusted P-Value	Correlation	P-Value	Adjusted P-Value
1-Month Historic Returns	**0.1028**	(0.01)	0.0830	(0.04)	(0.24)	0.0087	(0.83)	(0.93)	0.0477	(0.25)	(0.75)	-0.0370	(0.37)	(0.87)
3-Month Historic Returns	**0.0747**	(0.07)	0.0456	(0.27)	(0.52)	-0.0284	(0.49)	(0.78)	0.0190	(0.65)	(0.90)	-0.0857	(0.04)	(0.69)
6-Month Historic Returns	-0.0005	(0.99)	-0.0297	(0.47)	(0.68)	-0.0379	(0.36)	(0.71)	-0.0091	(0.83)	(0.95)	-0.1373	(0.00)	(0.53)
12-Month Historic Returns	0.0430	(0.30)	0.0165	(0.69)	(0.82)	-0.0147	(0.72)	(0.89)	-0.0759	(0.07)	(0.61)	-0.2325	(0.00)	(0.28)
24-Month Historic Returns	-0.0422	(0.31)	-0.0869	(0.04)	(0.23)	-0.1384	(0.00)	(0.18)	-0.2277	(0.00)	(0.12)	**-0.3696**	(0.00)	(0.08)
36-Month Historic Returns	-0.0485	(0.25)	-0.1082	(0.01)	(0.14)	**-0.1884**	(0.00)	(0.07)	**-0.3041**	(0.00)	(0.04)	**-0.4259**	(0.00)	(0.04)
48-Month Historic Returns	**-0.0992**	(0.02)	**-0.1775**	(0.00)	(0.02)	**-0.2424**	(0.00)	(0.02)	**-0.3340**	(0.00)	(0.02)	**-0.4187**	(0.00)	(0.05)
60-Month Historic Returns	**-0.0730**	(0.09)	**-0.1536**	(0.00)	(0.04)	**-0.2375**	(0.00)	(0.02)	**-0.3053**	(0.00)	(0.04)	**-0.2630**	(0.00)	(0.25)

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Table 5.4 Correlations between Dependent Returns and Independent Valuation Variables

	Momentum Variables – Long-Term P/E Deviations													
	1 Month Returns		3 Month Returns			6 Month Returns			12 Month Returns			24 Month Returns		
	Correlation	P-Value	Correlation	P-Value	Adjusted P-Value	Correlation	P-Value	Adjusted P-Value	Correlation	P-Value	Adjusted P-Value	Correlation	P-Value	Adjusted P-Value
Deviation from 3 Year P/E MA	-0.0059	(0.89)	-0.0357	(0.40)	(0.63)	-0.0627	(0.14)	(0.55)	-0.0639	(0.13)	(0.67)	-0.1399	(0.00)	(0.53)
Deviation from 5 Year P/E MA	-0.0286	(0.51)	-0.0719	(0.10)	(0.34)	-0.1162	(0.01)	(0.28)	-0.1486	(0.00)	(0.34)	-0.2462	(0.00)	(0.28)
Deviation from 10 Year P/E MA	-0.0490	(0.28)	-0.0860	(0.06)	(0.28)	-0.1180	(0.01)	(0.30)	-0.1373	(0.00)	(0.41)	-0.2153	(0.00)	(0.38)

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Table 5.4 Correlations between Dependent Returns and Independent Valuation Variables

% Difference from 3 Year P/E MA	-0.0028	(0.95)	-0.0313	(0.46)	(0.67)	-0.0574	(0.17)	(0.58)	-0.0591	(0.17)	(0.70)	-0.1400	(0.00)	(0.53)
% Difference from 5 Year P/E MA	-0.0250	(0.56)	-0.0681	(0.11)	(0.36)	-0.1156	(0.01)	(0.28)	-0.1560	(0.00)	(0.31)	-0.2640	(0.00)	(0.24)
% Difference from 10 Year P/E MA	-0.0516	(0.26)	-0.0933	(0.04)	(0.24)	-0.1319	(0.00)	(0.25)	-0.1593	(0.00)	(0.33)	-0.2191	(0.00)	(0.37)

Table of Correlations (adjusted and unadjusted p-values in brackets). All bolded figures are significant at the 10% level. ALSI Sample Period: 1 January 1960 – 31 January 2010. Earnings Yield is measured as EPS/P. Dividend Yield is measured as DPS/P. RLRS Adjusted Earnings Yield is measured as Earnings Yield/RLRS. RLRS Adjusted Dividend Yield is measured as Dividend Yield/RLRS. RBAS Adjusted Earnings Yield is measured as Earnings Yield/RBAS. RBAS Adjusted Dividend Yield is measured as Dividend Yield/RBAS. T-Month Earnings Growth is measured as ln(EPS(t))-ln(EPS(t-T)). Term Spread is calculated as RLRS – RBAS. % Overbought/Sold Indicator is measured as $(P_t-MA_t)/MA_t$. T-period historic returns are calculated as $\ln(ALSI_t)-\ln(ALSI_{t-T})$. Deviation from moving average is calculated as (PE_t-MA_t). % difference from moving average is calculated as $(PE_t-MA_t)/(MA_t)$.

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Valuation Measures

Both adjusted and unadjusted earnings yields are positively correlated with all return horizons and the unadjusted earnings yield has a significant, at the 10% level, relationship with all future return horizons, using both the unadjusted and adjusted test values. This finding of positive correlation with future returns is consistent with the findings of Campbell and Shiller (1998). The adjusted strength of the correlation grows slightly stronger from one to three month returns, before deteriorating slightly for six month and longer returns. Of the adjusted earnings yields, only the RBAS adjusted earnings yield has a significant relationship with one and three month returns, using the adjusted test values.

Both adjusted and unadjusted dividend yields are positively correlated with all return horizons. However, using the adjusted test values, none of these relationships are significant at the 10% level.

To conclude, of the earnings variables, only earnings yield (for all return horizons) and RBAS adjusted earnings yield (for one and three month return horizons) can be considered as suitable predictive factors to be utilised in a multifactor forecast model.

Growth Measures

The correlation between earnings growth and future returns is positive, but not significant at the 10% level, for short-term returns (1 & 3-month), and only when using the shorter earnings growth measures (6 & 12-month for 1 & 3-month returns, 18-months for 1-month returns), with all longer-term returns having negative correlations. Earnings growth measured over more than 18-months is negative for all return horizons. This suggests that times of high earnings growth will be followed by lower future returns, either due to past overconfidence or due to the cyclical nature of the economy. However, the majority of the correlations are not significant, at the 10% level, using the adjusted test statistics, with 24-month earnings growth having a significant correlation with 12 and 24-month returns and 36-month earnings growth having a significant correlation with 12-month returns. Due to the fact that 24-month earnings growth is significant with both of the long-term return horizons, and that it is more correlated to 12-month returns relative to 36-month returns, this variable should be considered as a factor in the multifactor model for the relevant timeframes.

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The correlations between the long-term gilt and future return horizons is positive, indicating that higher interest rates should lead to higher returns; a fact that is consistent with an equity premium where return on equity = return on risk-free asset + premium. However, none of the correlations are significant at the 10% level using the adjusted test-statistics, so the variable should not be included in the multifactor forecast models.

The correlations between the short-term discount rate are negative for 1 and 3-month return horizons and positive for longer return horizons. The short-term negative correlations are inconsistent with the equity premium, but movements in the short-term interest rates may reflect investor confidence, which could potentially explain this result. However, none of the correlations are significant at the 10% level using the adjusted test-statistic, so the variable should not be included in the multifactor forecast models.

The correlations between the term spread and future returns are positive, as expected, for 1 to 12-month return horizons and negative for 24-month return horizons. However, none of these correlations are significant, at the 10% level, using the adjusted test-statistics, so the variable should not be included in the multifactor forecast models

Momentum Measures

The correlations between the short-term overbought/sold indicators are positive for 1, 3 and 12-month future returns and negative for 6 and 24-month negative returns. This suggests that, for certain returns, there is a momentum effect, as an overvalued (relative to its moving average) ALSI is followed by positive returns, and vice versa. However, these correlations indicating short-term momentum are only significant, at the 10% level, for 1-month future returns. Of these, the 90-day overbought/sold has the highest correlation, and, unless there is limited multicollinearity between it and the other short-term overbought/sold indicators, should be included in the 1-month multifactor forecast model.

The correlations between long-term overbought/sold indicators and future returns is generally negative, with only the 1-year overbought/sold correlation with 1 and 3-month returns and the 3-year overbought/sold correlation with 1-month returns positive. This suggests that, in general, the market reverses long-term movements away from the moving average. However, only six correlations are significant at the 10% level, using

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the adjusted test-statistics. These are the 3-year overbought/sold indicator with 24-month returns, the 5-year overbought/sold indicator with 6, 12 and 24-month returns and the 10-year overbought/sold indicator with 6 and 12 month returns. The highest correlation is the 5-year overbought/sold indicator with all three of the return horizons, and should be included for 6, 12 and 24-month multifactor forecast models.

There are positive correlations for 1 and 3-month historic returns with 1, 3, 6 and 12-month future returns, with the exception of 3-month historic returns and 6-month future returns, which has a negative correlation. This implies a momentum effect, with movements in the ALSI continuing in the short-term future. However, only the correlations with 1-month future returns are significant, at the 10% level, using the adjusted test-statistics. The 1-month historic return has the highest correlation with 1-month future returns and should be considered as a factor in the 1-month multifactor forecast model.

All correlations for 6-month and longer historic returns are negative, with the exception of 12-month historic returns and 1 and 3-month future returns. This indicates a reversal effect, where long-term movements in one direction are reversed over the following period. Many of the correlations are significant, at the 10% level, using the adjusted test-statistics. However, due to the likely high level of multicollinearity between the varying constructions of the variable, the inclusion of only one long-term historic return would be preferable. 48-month returns have the highest correlation for short-term (1, 3 and 6-month) future returns, and should be considered in the respective return horizons' multifactor forecast model. For longer-term horizons, 48-month historic return has the highest correlation with 12-month future returns and 36-month historic returns for 24-month future returns. For simplicity, 36-month historic returns will be used for the long-term variables to allow for easier comparison.

All the varying measures of movement away from the long-term price/earnings ratio have a negative correlation with future returns, indicating that over or undervaluation relative to the historic price/earnings ratio will lead to a future correction. However, none of the variables are significant, at the 10% level, using the adjusted test-statistic, with any future returns, meaning that the inclusion of this variable in a multifactor forecast model would be unnecessary.

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Summary of Correlations

The correlations calculated between the numerous potential predictive variables and the varying return horizons show that there are only a few that are significant predictors of future returns. Only earnings yield and long-term historic returns are significant with all future return timeframes. Earnings yield adjusted for the 90-day bankers discount rate is only significant with 1 and 3-month future returns. Long-term earnings growth is significantly related to future 12 and 24-month returns, while none of the interest rate variables have any significant relationships with future returns. Short-term overbought/sold indicators are only significant with 1-month future returns, while long-term overbought/sold indicators are only significant with 6, 12 and 24-month future returns. Short-term historic returns are only significantly related with 1-month returns, long-term historic returns are significant across return horizons, while none of the P/E deviations from moving average variables are significant.

The table below illustrates which variables will be analysed further for possible inclusion in the multifactor forecast model of the relative return timeframe. They are ordered in descending order of the absolute value of their correlation.

Table 5.5 Variables selected for Multifactor Forecast models

1-Month Returns	3-Month Returns	6-Month Returns	12-Month Returns	24-Month Returns
1-Month Historic Return	48-Month Historic Return	48-Month Historic Return	5-Year Overbought/Sold Indicator	5-Year Overbought/Sold Indicator
48-Month Historic Return	Earnings Yield	5-Year Overbought/Sold Indicator	36-Month Historic Return	36-Month Historic Return
90-Day Overbought/Sold Indicator	RBAS Adjusted Earnings Yield	Earnings Yield	Earnings Yield	Earnings Yield
RBAS Adjusted Earnings Yield			24-Month Earnings Growth	24-Month Earnings Growth
Earnings Yield				

Variables selected for further analysis, ordered in descending order of absolute value of correlation.

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The above table shows several trends. The first is that momentum variables have the strongest relationships with future returns, regardless of time horizon. For 1-month returns, this indicates that there are short-term momentum and long-term price reversal effects, while for longer return horizons, it is only long-term price reversals that are able to predict future returns.

Valuation variables prove to be the next strongest indicator of future returns. Earnings yield has a significant relationship, at the 10% level, with all future returns, while RBAS adjusted earnings yield is significant at the 10% level for 1 and 3-month returns.

Growth variables are the weakest indicators of future returns. Earnings growth is only a significant, at the 10% level, predictor of 12 and 24-month returns, and in both return horizons, it is the weakest predictor relative to the other candidate variables.

5.2 Analysis of Candidate Independent Variables and Returns

The correlation analysis above provides the starting framework for the construction of a multifactor model. However, greater analysis of the candidate independent variables for suitability is required before their final inclusion in the models. This analysis has four components (5.2.1-5.2.4): a visual analysis of the variable and the ALSI, a unit root test to ensure that both dependent and independent variables are stationary, an analysis of two sub-samples to test for the presence of a structural break, and finally, a table of correlation of the independent variables to check for the presence of multicollinearity. At the end of these analyses, the results are summarised in a conclusion (5.2.5).

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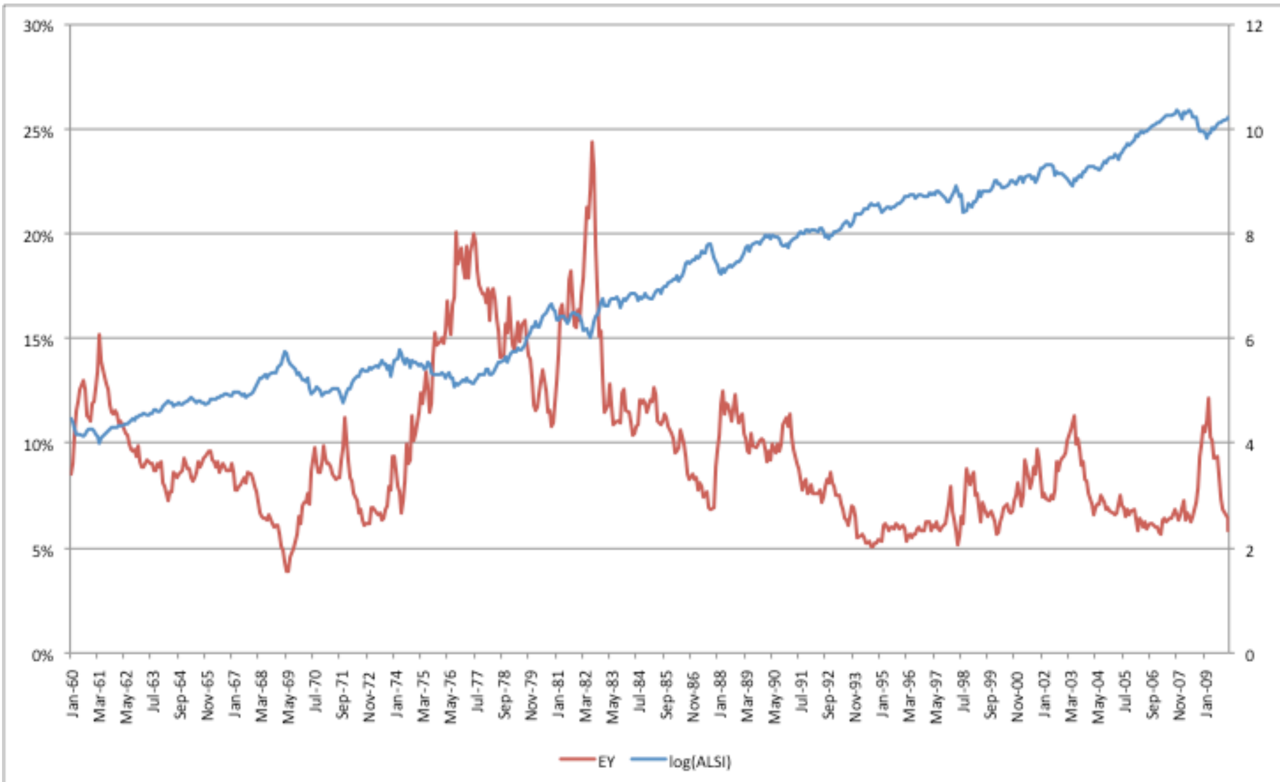
5.2.1 Visual Analysis of Chosen Variables and the ALSI

Figure 5.3 Earnings Yield and the JSE ALSI



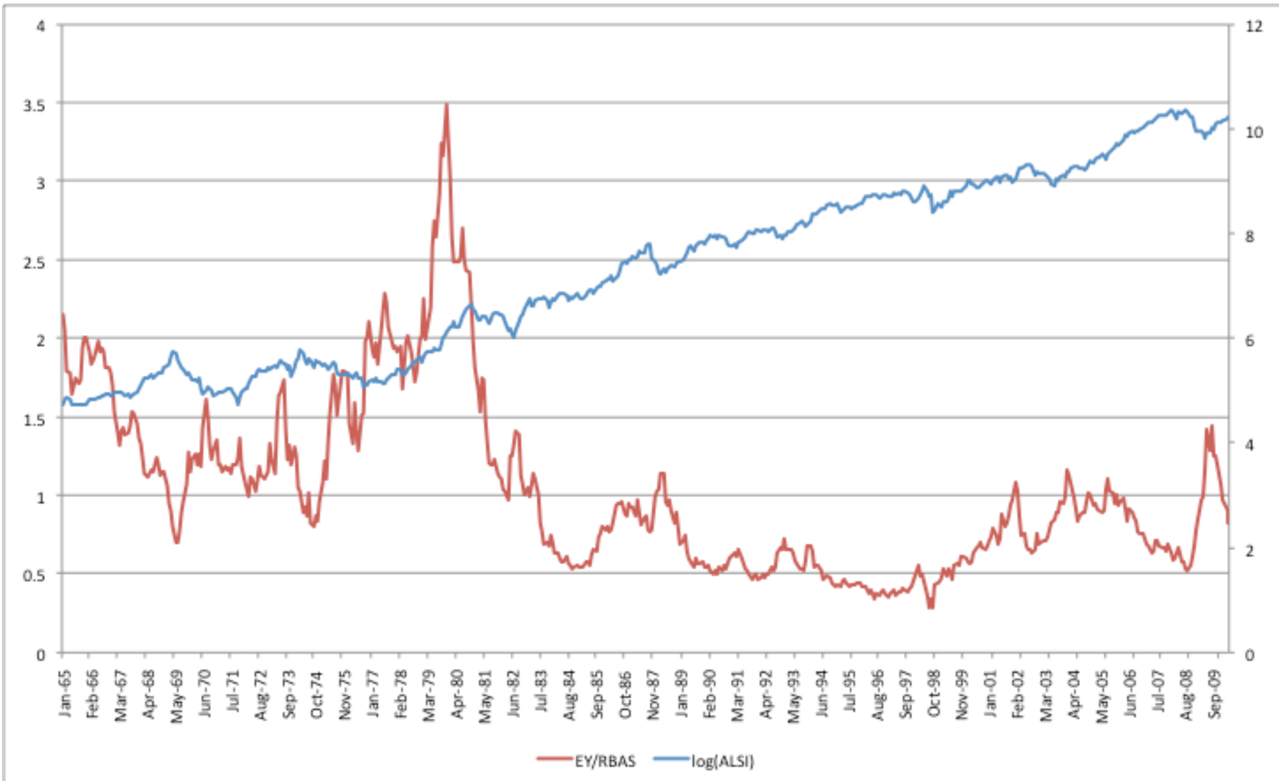
From an analysis of the above graph, it appears that earnings yield foreshadows the movement of the ALSI. Earnings yields tend to decline, by construction, as the market runs up to a peak, before rapidly increasing as the market reverses from a prior high. As such, if there are lower earnings yield, any future increases in prices are less likely and will occur at a slower rate, while higher earnings yields are followed by higher returns as the share price corrects to a value more accurately representing the underlying market dynamics. It also appears that there is lower volatility in earnings yield after 1982, with earnings yields falling in the range of 5 to 13%. However, over the entire sample, earnings yield have only breached 15% on 3 occasions: briefly in 1961, for most of the period between 1975-1979 and for several months between 1981-1982. The first occasion (during 1961) is the simplest to explain: as earnings represents performance over the past 12-months, it is backwards looking. However, the market is forward-looking. During 1961, the market declined sharply as future expected earnings decreased. Earnings on the other hand, remained relatively unchanged. As such, the market was priced less expensively, and the earnings yield increased. For the period between 1975-1979, the South African economy had grown steadily over the past 10 years, with real GDP growth averaging 4.73%. However, the economy stagnated over the next 5 years, with average real GDP growth at 2.1% between 1975 and 1980. The lower growth over the period led to a downward revision in growth prospects, and therefore stock prices, leading to a higher earnings yield. With signs of an economic boom at the end of 1979, expected earnings growth was revised upwards, leading to more expensively priced shares relative to earnings and a lower earnings yield. However, this optimism was short-lived as gold prices declined over a period of years from a high of just below 850/ounce to R350/ounce.

Figure 5.4 Earnings Yield and Gold Price (in Rands) from 1980 – 1984

Due to the combination of this collapse in the gold price and the resource dependent nature of the JSE ALSI, the expected earnings growth for the index was revised downwards, leading to earnings yields again increasing to above 15%. These earnings yields were maintained until the gold price reverted over several months to a level close to its previous high, when investors once again became more optimistic about future earnings growth, leading to stocks being more expensively priced relative to their historic earnings.

After this last period, earnings yield has remained in a narrower range. Even during the sub-prime caused recession, earnings yield only briefly spiked above 10% before returning to its normal range, indicating that deviations from the long-term trend are smaller and shorter in the past few decades than in previous decades.

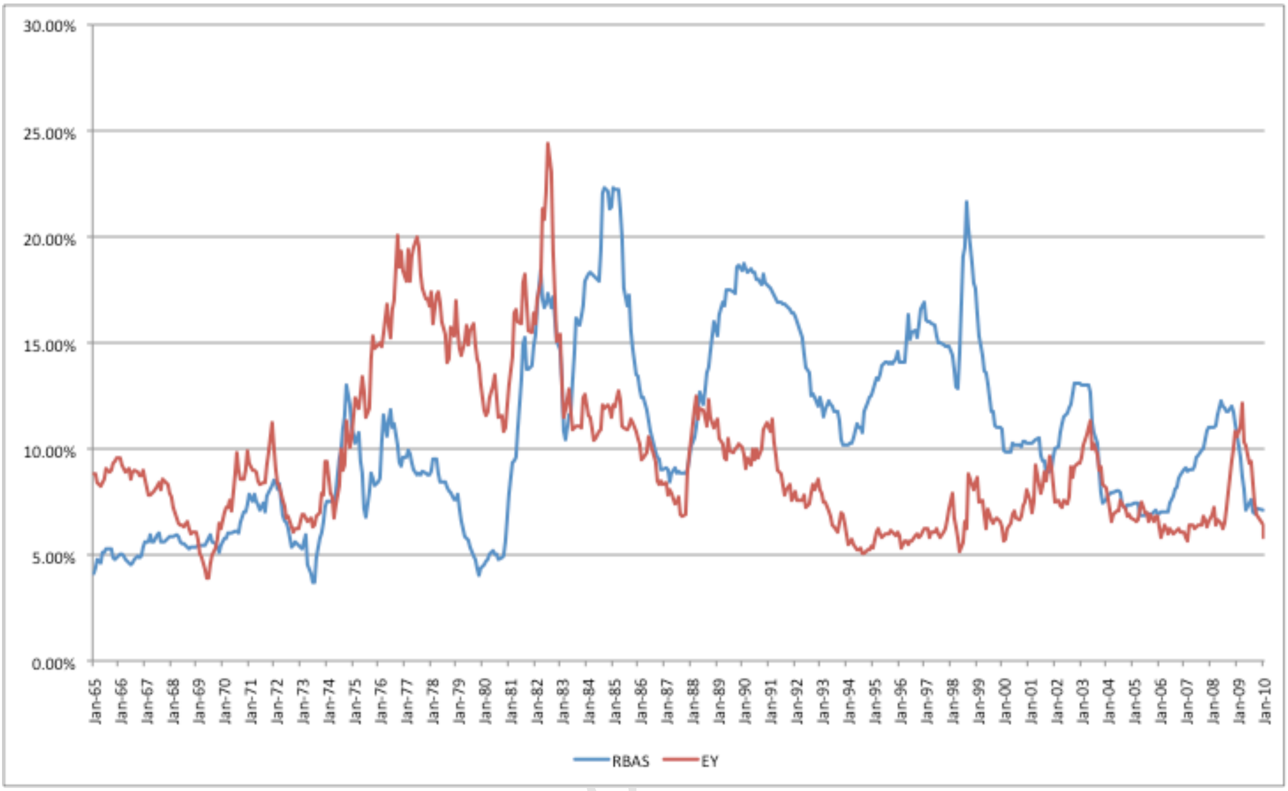
Figure 5.5 RBAS Adjusted Earnings Yield and the JSE ALSI



After sharp drops, the RBAS adjusted earnings yield tends to increase. As these sharp downturns tend to be corrected in the next period, there seems to be a relationship with high RBAS adjusted earnings yields and high short-term returns. During long-running bull periods, the adjusted earnings yield tends to decline. Therefore a low adjusted earnings yield indicates that short-term returns are either going to be fairly low (as the bull reaches its peak) or negative (as a long-term correction occurs).

Like earnings yields, adjusted earnings yield are more stable and vary within a smaller range after the crisis in the early 1980s, when the earnings yield on the JSE ALSI was three and half times the RBAS. To understand the dynamics, a graphical history of the two components of adjusted earnings yield, earnings yield and RBAS, are provided below.

Figure 5.6 RBAS and Earnings Yield



Movements in the earnings yield have already been analysed above. One finding is that after 1983, the 90-Day Bankers' Discount Rate has generally been equivalent or greater than the earnings yield on the JSE ALSI (which can be seen in Figure 5.2.1.3 as the adjusted RBAS rarely breaches a value of 1 over this time period). As this implies that the rate of return on a near risk-free asset has been less than the implicit yield of the risky index of securities on the JSE ALSI, this is a curious finding. Of course, earnings yield is merely a ratio of earnings relative to price and does not factor in any expected increases in the level of the JSE ALSI, so this finding could indicate a movement through time from implicit value returns generated by earnings through dividends to returns generated by price movements.

There also appears to be two structural breaks in the RBAS over the time period. Between 1965 and 1981, the RBAS fluctuated between 5 and 10%, except for short periods after the oil shocks and inflation of 1973 and 1979, which in turn increased nominal interest rates. From 1981 to 1999 the RBAS fluctuated between 10 and 25% (with the exception of several years between 1985 and 1988). After 1999, the RBAS once again fluctuated between 5 and 15%. Whether this is a true structural break of the RBAS or a structural break of the fundamental economic drivers of the RBAS is unclear without an analysis that goes beyond the scope of this study, but it is plausible that the political instability in the 1980s (Fielding, 2001) drove interests rate higher to compensate for the additional risk. However, this argument is unsuccessful in explaining the higher discount rates that occurred in the post-Apartheid period. But, apart from 1996 and 1998, the RBAS mostly falls within the 5-15% range. The data from 1996 and 1998 could be considered as outliers: the first due to tight monetary policy being implemented by the South African Reserve Bank due to the Rand crisis and the second caused by a sharp tightening of monetary policy by the South African Reserve Bank in response to the rapidly depreciating rand that occurred as a result of the Asian and Russian financial crises (Kahn & Farrell, 2002: 15). Both were shocks to the South African economy and financial markets but neither of the shocks persisted for a sustained period thereafter, which indicates that a structural break is not present. With the South African Reserve Bank's inflation targeting policy beginning in 2002, shocks like these have generally been accompanied with a prior increase in interest rates, as the Reserve Bank attempts to curb overheating of the economy, followed by a sharp decrease in interest rate after a shock, as inflation falls sharply due to a crisis. This is most clearly evident in the most recent sub-prime crisis of 2008-2009, where interest rates increased consistently from 2006-2008, before dropping sharply in an attempt to stimulate the economy in the low-inflation environment that arose after the sub-prime crash.

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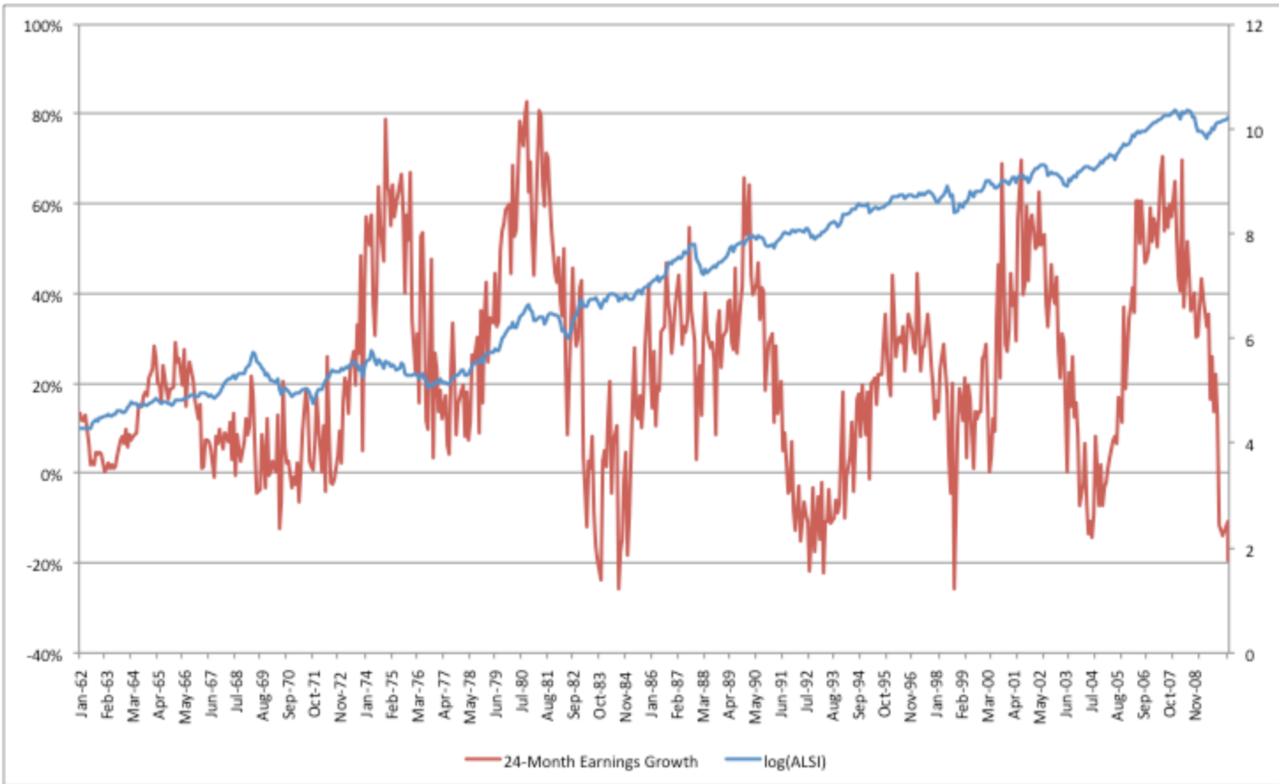
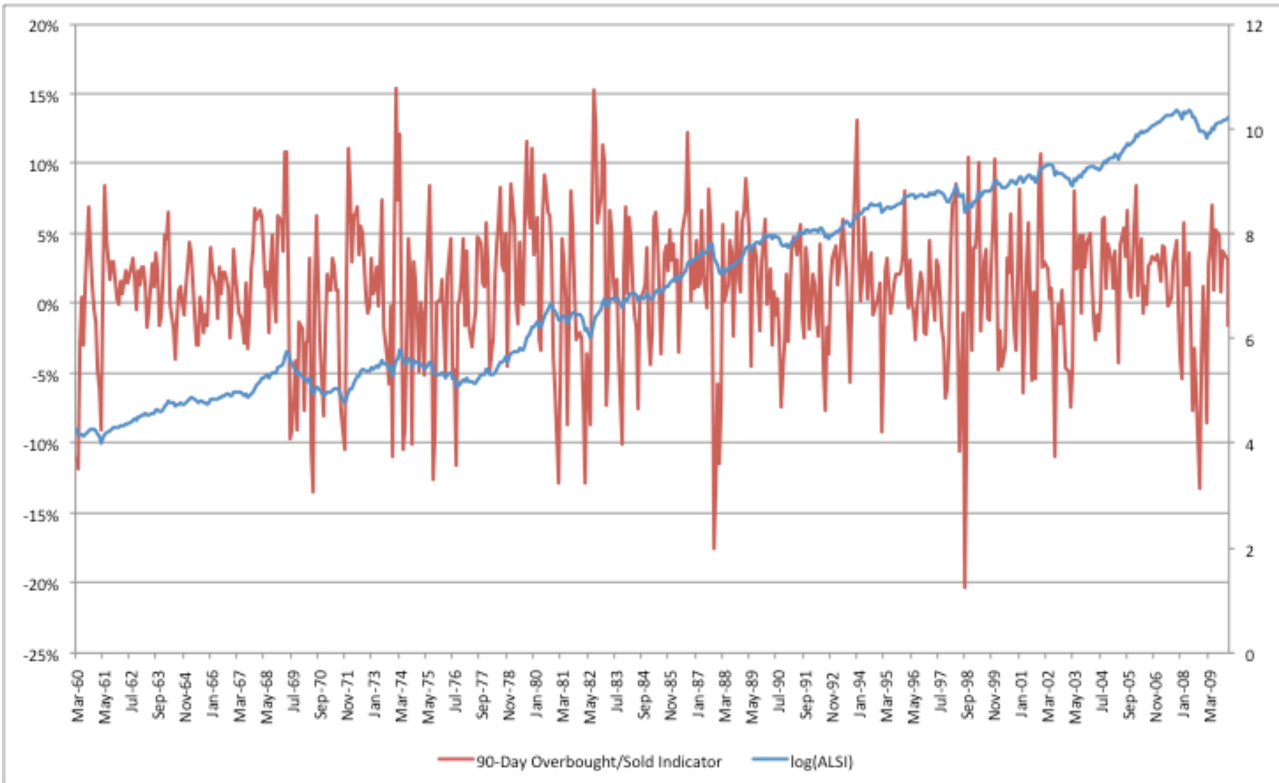
Figure 5.7 24-Month Earnings Growth and the JSE ALSI



The pattern of earnings growth through time is cyclical, which is to be expected, as earnings are a function of the business cycle. It is also evident that there is a sharp decline in the JSE ALSI within a few years of earnings growth breaching 40% over a 2-year period. After the decline, earnings growth tend to remain at the relative low for several months, and it is during this stage that the JSE ALSI often has its largest returns, as the market reverses the losses that often occur due to irrationality during a crash period. Thus, the visual evidence suggests that the negative correlation between earnings growth and long-term returns found above is a valid finding.

Apart from the cyclical nature of earnings growth, a visual analysis indicates that earnings growth over a 2-year period is generally positive. On six occasions earnings growth became negative: in the late 1960s-early 1970s, in the early 1980s, in the early 1990s, briefly during 1998, during 2004-2005 and most recently during the sub-prime crisis and the subsequent recession. Most of these have been explained above as major bust periods that either affected South African firms directly (due to declines in the economy and major drivers of earnings) or indirectly due to contagion from a global problem (Asian and Russian Financial Crisis and Sub-Prime Crisis). Apart from these shocks, earnings tend to grow through time, although the rate of growth itself varies due to the economic cycle. This is to be expected as firms seek investments that will earn a yield that exceeds their required rate of return, which in itself is the sum of a risk-free rate and a risk premium. Thus, realised returns should approximate expected returns on average, leading to an upward trend on earnings and therefore generally positive earnings growth.

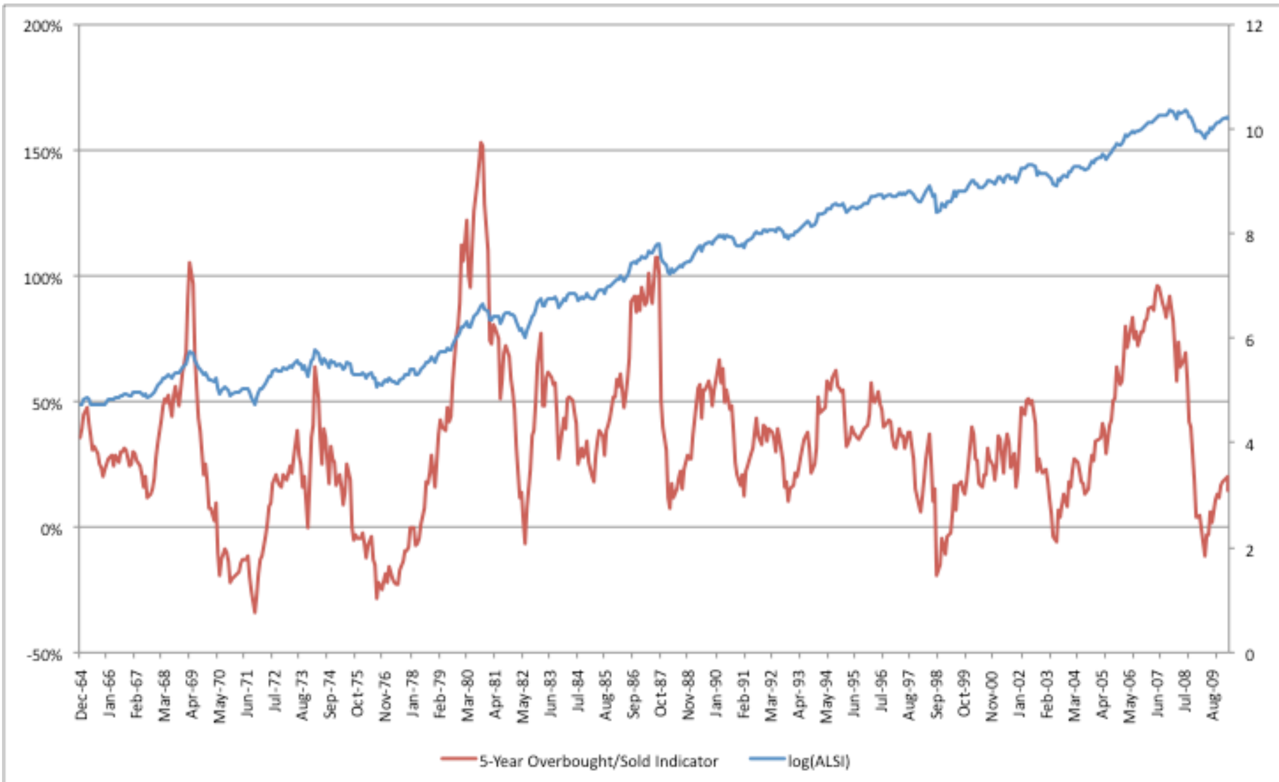
Figure 5.8 90-Day Overbought/Sold Indicator and the JSE ALSI



Due to the volatility in short-term variables, the relationship between the short-term overbought/sold indicator and short-term returns is not clearly visible from a visual analysis.

The pattern of the overbought/sold indicator suggests great short-term variability in the relative value of the JSE ALSI. There are also two clear findings. The first is that there are more positive observations than negative observations, with the range between 0 and 5% being the most heavily populated. This is intuitive as the JSE ALSI trends upwards through time and should, in most cases, be slightly overvalued relative to its short-term moving average. The second is that largest deviations from relative value are on the downside, in 1987 and 1998, both times breaching the -15% mark and both occurring in times of a severe financial crisis. This indicates that short-term negative shocks have a greater absolute effect on the JSE ALSI compared to positive shocks.

Figure 5.9 5-Year Overbought/Sold Indicator and the JSE ALSI



Unlike the short-term overbought/sold indicator, the 5-year overbought/sold indicator is less volatile, allowing trends and relationships to be inferred by visual analysis. Like earnings growth, there is clear cyclicality in this relative value measure, with swings from large relative overvaluation to undervaluation, and vice versa. There appears to be a relationship between these swings and movements in the JSE ALSI, as sharp declines in the JSE ALSI normally follow periods of severe overboughtness (in the early 1980s, over 150%). After these declines, the relative value tends to be negative, and is followed by price movements upwards as an over-reaction to a crisis is corrected and the JSE ALSI moves closer to its fundamental value. This finding reinforces the initial finding of a negative correlation between the long-term overbought/sold indicator and long-term returns.

The swings in the long-term overbought/sold indicator appear to occur due to the same reasons as those affecting earnings yield variables and earnings growth, with the exception of a sharp decline in October 1987.

October 1987 was the month of Black Monday, a market shock without warning or any clear reason that corrected itself shortly. The relative value of the JSE ALSI is generally positive, which is intuitive as the JSE ALSI has a positive expected return of inflation plus an additional risk premium and, in the long-term, actual and expected returns should approximately equal one another. However, there are several periods where there are negative relative valuations, which suggest that any decline in the JSE ALSI persists for several months or years after the initial shock, instead of correcting rapidly. However, the longest periods occurred in the 1970s when there was a general stagnation in the JSE ALSI, and this phenomenon has only occurred on a smaller scale after this period.

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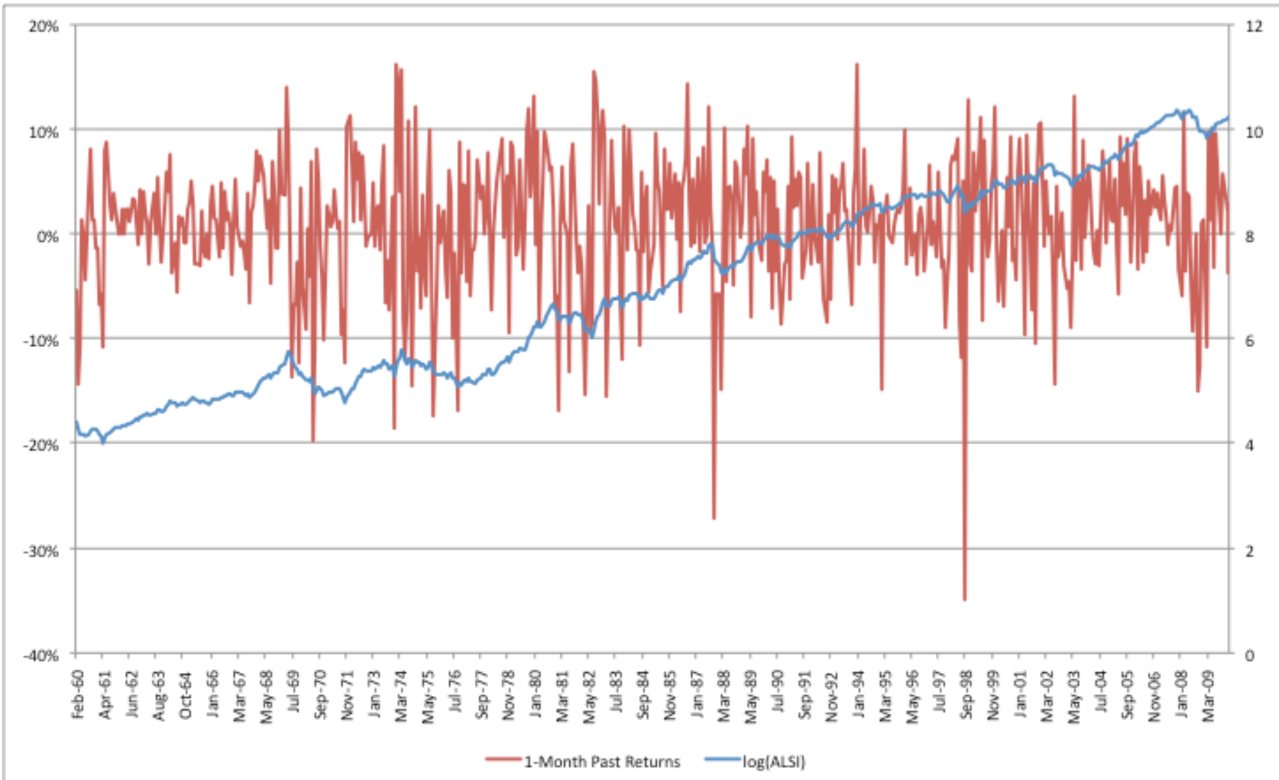
Figure 5.10 1-Month Past Returns and the JSE ALSI



Like the short-term overbought/sold indicator, short-term return history is too volatile to allow for any relationships to be inferred from a visual analysis.

Like the short-term overbought/sold indicator, the largest proportion of observations occurs within a narrow positive range between 0 and 10%, which is again an intuitive result as the JSE ALSI is expected to be an upward trending series. However, like the short-term overbought/sold indicator, the largest one-month movements in the JSE ALSI are on the downside, as are the majority of movements in absolute terms of more than 10%. This once again suggests that there is more downside risk in short-term JSE ALSI returns than a normal distribution would suggest (a longer negative tail compared to positive tail). It also suggests that if an investor can correctly predict negative returns and move into an alternative, risk-free investment, then returns significantly in excess of the JSE ALSI can be generated, with much lower risk.

Figure 5.11 36-Month Past Returns and the JSE ALSI

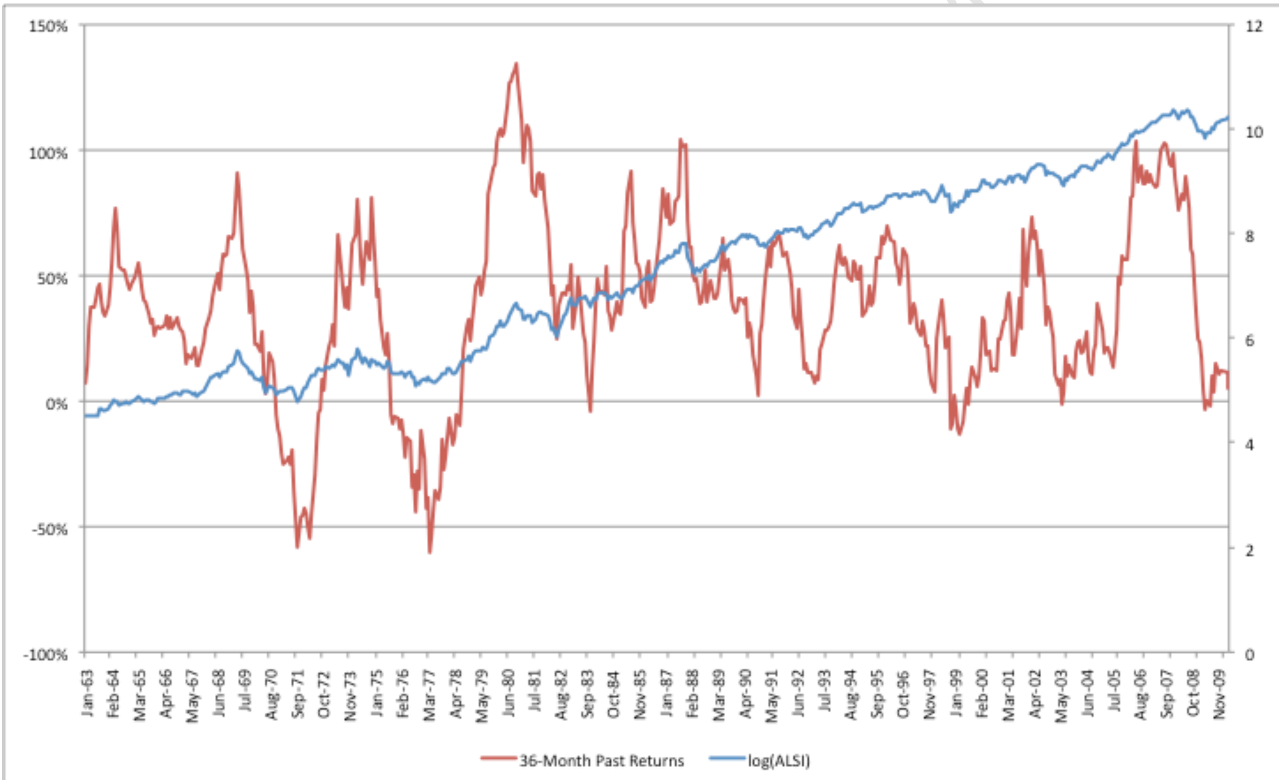
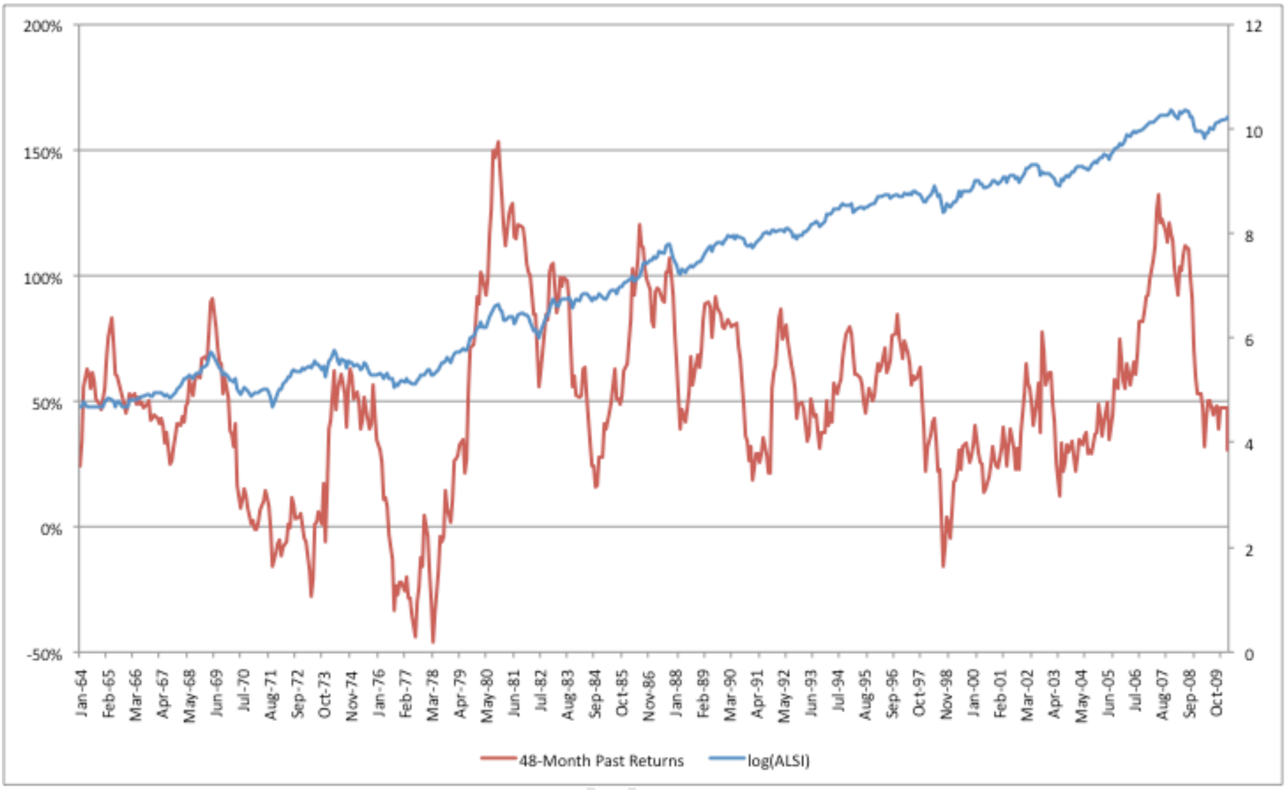


Figure 5.12 48-Month Past Returns and the JSE ALSI



Due to the longer time horizon, 36 and 48-month returns are less volatile and clear trends are visible from a visual analysis. Despite the difference of a year in the timeframes, the patterns are very similar and are analysed concurrently.

Like the long-term overbought/sold indicator, long-term historic reasons are cyclical in nature, with large positive historic returns followed by small or even negative returns. There also appears to be periods where historic returns grow at a steady rate, before accelerating rapidly as a bull market peaks, before sharply declining. Thus, like the long-term overbought/sold indicator, large positive historic returns are generally followed by negative returns (as the market corrects from months or years of overvaluation) and when there are negative returns, the market tends to have positive returns for the subsequent months as the market corrects the downside overreaction and the market returns to a level closer to its fundamental value. This finding reinforces the finding of a negative correlation between long-term historic returns and future returns.

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The upward trend in JSE ALSI returns is evident from the longer-term returns, with fairly few periods of negative returns. For 36-month historic returns, there are negative returns in five periods, twice in the 1970s in a stagnant economy, briefly during 1983 when the gold price fell dramatically, briefly during 1998 as an indirect result of the Asian and Russian financial crisis, briefly during 2003 as a commodity cycle reversed and briefly in 2008/2009 as a result of the recession caused by the sub-prime crisis. 48-month returns are negative in three periods, twice in the 1970s and briefly in 1998, for the same reasons as those that affected 36-month returns. The fewer negative returns and the generally higher level of returns over this time period indicate that longer investment horizons are more likely to lead to a positive and stable return closer in line with expected returns than the return that is realised for shorter investment horizons. However, there is still clear advantages in timing entry and exit to long-term strategies, as entering at the bottom of cycle and exiting at the top of the cycle will lead to superior returns.

5.2.2 Unit Root Tests of Dependent and Independent Variables

The use of non-stationary variables in a regression analysis can lead to spurious results. Therefore it is imperative to check that all variables are stationary. For this dissertation, the augmented Dickey-Fuller Test is used to test for unit roots, defined as $\Delta Y_t = \beta_0 + \beta_1 t + \delta Y_{t-1} + \sum_{i=1}^{m} \alpha_i \Delta Y_{t-1} + \varepsilon_t$ (Gujarati, 2003). The results of these tests are shown below.

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Table 5.6 Results of Unit Root Tests

Variable	t-Statistic	p-Value
Dependent Variables		
1-Month Returns	**-22.0483**	(0.00)
3-Month Returns	**-6.7551**	(0.00)
6-Month Returns	**-6.9594**	(0.00)
12-Month Returns	**-7.6747**	(0.00)
24-Month Returns	**-3.8617**	(0.00)
Independent Variables		
Earnings Yield	**-2.6233**	(0.09)
RBAS Adjusted Earnings Yield	**-2.6326**	(0.09)
24-Month Earnings Growth	**-3.0353**	(0.03)
90-Day Overbought/Sold Indicator	**-11.5317**	(0.00)
5-Year Overbought/Sold Indicator	**-3.7050**	(0.00)
1-Month Returns	**-22.0483**	(0.00)
36-Month Returns	**-3.3159**	(0.01)
48-Month Returns	**-3.2325**	(0.02)

Table of t-Statistics (p-Values in brackets), calculated using the Augmented Dickey Fuller Test with a maximum lag of 10. Bolded figures are significant (stationary) at the 10% level.

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The results of the unit-root tests show that, at the 10% significance level, no dependent or independent variable has a unit root. One can therefore conclude that the variables are stationary and can be used in ordinary least-squares regression.

5.2.3 Sub-Sample Analysis

Although the results gathered from the earlier parts of this study indicate that there are certain correlations that could be useful in predicting the JSE, these results are gathered over the entire sample period. It is therefore useful to break the sample period into two individual sub-samples, 1960-1985 and 1985-2010, and analyse the candidate variables performance in each sub-sample. The first step in this process is to collect and compare the means and standard deviations of the candidate variables before and after 1985. Below is a table of the pre and post-1985 means and standard deviations of all independent and candidate dependent variables.

Table 5.7 Pre and Post-1985 Averages of Variables

Dependent Variables	Pre-1985		Post-1985	
	Mean	St Dev	Mean	St Dev
1-Month Returns	0.0133	0.0639	0.0133	0.0611
3-Month Returns	0.0407	0.1208	0.0404	0.1093
6-Month Returns	0.0827	0.1703	0.0814	0.1594
12-Month Returns	0.1653	0.2361	0.1616	0.2168
24-Month Returns	0.3352	0.3451	0.3318	0.2578

Independent Variables	Pre-1985		Post-1985	
	Mean	St Dev	Mean	St Dev
Earnings Yield	0.1118	0.0387	0.0774	0.0177
RBAS Adjusted EY	1.4341	0.5773	0.6891	0.2238
24- Month Earnings Growth	0.2169	0.2243	0.2421	0.2123
90 Day Overbought/Sold	0.0089	0.0506	0.0111	0.0459
5-Year Overbought/Sold	0.2949	0.3512	0.3854	0.2573
1-Month Returns	0.0133	0.0639	0.0133	0.0611
36-Month Returns	0.5022	0.3942	0.5098	0.2676
48-Month Returns	0.6536	0.4103	0.6935	0.2810

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From an analysis of the table above, it would appear that returns for return horizons less than 36 months are, on average, slightly smaller after 1985. However return horizons greater and equal to 36-months have, on average, slightly larger returns after 1985. This result can be explained due to differences in the starting of each return horizon series. More conclusively, across return timeframes, standard deviations are substantially smaller after 1985, indicating lower return volatility, and therefore lower risk. Average earnings yield is roughly 3.5% smaller after 1985 and its standard deviation is roughly half its pre-1985 value, indicating that the ALSI is valued higher relative to earnings. The average earnings yield adjusted for the 90-day bankers discount rate after 1985 is less than half the pre-1985 value and switches from greater than one to less than one, implying that the yield on short-term risk-free assets becomes greater than the implicit yield of the ALSI after 1985. The standard deviation on the adjusted earnings yield is also smaller after 1985; a result that is unsurprising as the variable is calculated using earnings yield, and earnings yield has lower volatility after 1985. Average 24-month earnings growth is roughly 3% higher after 1985, indicating that companies have grown faster in this period, which in turn indicates a stronger economic environment. The averages of the overbought/sold indicators are larger after 1985, indicating again that the ALSI is valued higher, this time relative to its moving average. The standard deviation is also once again smaller, implying that returns fit a closer trend above their moving averages after 1985.

Although some of these factors suggest that the market has become overvalued after 1985 relative to the period before 1985, average earnings growth has also increased. This suggests that there has been greater economic growth after 1985, which could indicate that the fundamental value of the JSE ALSI itself would itself also be higher as the market prices in the increased future growth prospects of the market.

Sub-Sample Correlation Analysis

The descriptive statistics above show that there are differences in both the dependent and independent variables in the two sub-samples. However, these statistics cannot indicate whether there has been any change in the relationships between independent and dependent variables.

A quick method to determine whether there have been any changes is to calculate the correlations of the variables in each sub-sample and see whether there are any changes. To make any visual changes easier to spot, the variables are ordered according to the absolute strength of the correlation, allowing any changes in relative

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strengths to be more visible. This also provides findings on the relationships in each individual sub-sample. This table is displayed below.

Table 5.8 Absolute Correlation Ordered Candidate Variables – 1960 to 1985

1-Month Returns		3-Month Returns		6-Month Returns		12-Month Returns		24-Month Returns	
RBAS Adjusted EY	(0.17)	RBAS Adjusted EY	(0.23)	Earnings Yield	(0.25)	Earnings Yield	(0.35)	Earnings Yield	(0.53)
1-Month Historic Returns	(0.16)	Earnings Yield	(0.19)	48-Month Historic Return	(-0.25)	36-Month Historic Return	(-0.30)	36-Month Historic Return	(-0.47)
90-Day Overbought/Sold	(0.13)	48-Month Historic Return	(-0.19)	5-Year Overbought/Sold	(-0.17)	5-Year Overbought/Sold	(-0.26)	5-Year Overbought/Sold	(-0.44)
Earnings Yield	(0.12)					24-Month Earnings Growth	(-0.21)	24-Month Earnings Growth	(-0.22)
48-Month Historic Return	(-0.10)								

Lists of coefficients analysed (correlations in brackets).

Table 5.9 Absolute Correlation Ordered Candidate Variables – 1985 to 2010

1-Month Returns		3-Month Returns		6-Month Returns		12-Month Returns		24-Month Returns	
RBAS Adjusted EY	(0.15)	RBAS Adjusted EY	(0.25)	**48-Month Historic Return**	(-0.28)	**5-Year Overbought/Sold**	(-0.41)	**24-Month Earnings Growth**	(-0.57)
48-Month Historic Return	(-0.12)	Earnings Yield	(0.21)	**Earnings Yield**	(0.28)	36-Month Historic Return	(-0.36)	**5-Year Overbought/Sold**	(-0.52)
Earnings Yield	(0.11)	48-Month Historic Return	(-0.19)	5-Year Overbought/Sold	(-0.27)	**Earnings Yield**	(0.32)	**36-Month Historic Return**	(-0.41)
90-Day Overbought/Sold	(0.05)					24-Month Earnings Growth	(-0.32)	**Earnings Yield**	(0.33)
1-Month Historic Return	(0.04)								

Variables selected for further analysis, ordered in descending order of absolute value of correlation. Bolded variables indicate a change in relative magnitude of the coefficient compared to 1960-1985.

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For 1-month returns, the two earnings yield variables and 48-month historic returns have fairly stable correlations in each individual sub-sample (the largest change being 0.02), with the earnings yield variables becoming slightly weaker in 1985-2010 while the long-term return variables correlation with future returns becoming slightly stronger. However, the correlations of the short-term momentum variables (1-month historic returns and 90 month overbought/sold indicator) with future 1-month returns are substantially lower in the second sub-sample. The relationship between 1-month historic and future returns is only a quarter as strong, while the overbought/sold indicator variable has less than half the relationship strength it has between 1960-1985. This suggests that the predictive relationship between the candidate variables and 1-month returns is different in the two sub-periods and any predictive relationship is potentially weaker after 1985.

The correlations between 3-month returns and the candidate independent variables retain the same ordering (in absolute terms) and the same signs. The actual magnitude of the correlation remains the same for 48-month historic returns and becomes slightly stronger for earnings yield and adjusted earnings yield. This evidence suggests that the predictive relationship between the candidate variables and 3-month returns is either stable across sub-periods or slightly stronger in the second sub-period.

The ordering of the correlation between 6-month returns and its candidate predictive variables changes slightly, with 48-month historic returns having a slightly more powerful relationship after 1985 relative to earnings yield. However, both variables have very similar correlations with 6-month returns before 1985 and both correlations strengthen by a magnitude approximating 0.03, suggesting that this finding is minor. The correlations between all candidate variables and 6-month returns retain the same sign across sub-periods. The 5-year overbought/sold variable strengthened significantly after 1985, with the magnitude increasing by approximately 0.1 in absolute terms and making the potential predictive relationship of this variable almost as powerful as the other two candidate variables. This evidence suggests that the correlations between the candidate variables and 6-month returns are stronger after 1985.

The ordering and the signs of the correlations of 12-month returns and its candidate variables differ across sub-periods. Earnings yield weakens slightly (while retaining the same sign) whereas the 5-year overbought/sold indicator increases significantly (and changes sign) after 1985, leading to the two variables switching places in

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relative order of absolute strength. The correlation between 36-month historic returns and 24-month returns strengthen slightly, while retaining the same sign, and 24-month earnings growth correlation with 12-month returns strengthens significantly, while changing sign, after 1985. Thus, the predictive power might be slightly stronger after 1985. However, the changes in the signs of some of the candidate variables' correlations suggest that there may have been a structural change in the relationship after 1985.

The ordering of 24-month returns and its candidate variables is entirely different after 1985. The strength of the correlation between earnings growth and 24-month returns more than doubles in the second sub-sample, while the strength of the 5-year overbought/sold indicator's correlation with future returns also increases, with both variables retaining the same sign. The strength of the correlation of 36-month returns and earnings growth with 24-month future returns declines after 1985, with the sign of the correlation for earnings growth changing. As there are two sets of opposite effects, the actual difference in predictive power is indeterminate. However, the larger increases in correlations after 1985 suggest that there is a slightly stronger predictive relationship between the candidate variables and 24-month returns. The change in signage of earnings growth is concerning as it suggests a structural break in the relationship.

To conclude, with the exception of 1-month returns, the evidence suggests that the predictive relationship between the candidate variables and their respective return timeframes is the same or stronger after 1985. There is also evidence, due to changes in the signs of certain correlations, that there may be a structural change in the relationship across the sub-periods. Therefore, a more rigorous investigation needs to be undertaken.

As a first technique to analyse relational changes in the two sub-samples, a correlation analysis (as above) is undertaken in the two individual sub-samples. A test statistic is calculated and then adjusted for the dependency following the same earlier method of dividing the number of observations by the square root of the months of the return timeframe. A probability is then calculated whether this correlation is significant at the 10% level. In addition, the test of significance of correlations is adjusted to account for the overlapping nature of long-term returns, as in 5.1.2. The table below provides the correlation adjusted probability values of the candidate variables throughout the whole sample, between 1960-1985 and between 1985-2010.

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Table 5.10 Correlation Analysis of Candidate Variable in Entire Sample and Sub-Samples

	1 Month Returns		3 Month Returns			6 Month Returns			12 Month Returns			24 Month Returns		
Earnings Yield	Correlation	P-Value	Correlation	P-Value	Adjusted P-Value	Correlation	P-Value	Adjusted P-Value	Correlation	P-Value	Adjusted P-Value	Correlation	P-Value	Adjusted P-Value
Whole Sample	**0.0847**	(0.04)	**0.1512**	(0.00)	(0.03)	**0.1982**	(0.00)	(0.05)	**0.2699**	(0.00)	(0.06)	**0.3931**	(0.00)	(0.06)
1960-1985	**0.1165**	(0.04)	**0.1945**	(0.00)	(0.05)	**0.2479**	(0.00)	(0.09)	**0.3481**	(0.00)	(0.10)	**0.5333**	(0.00)	(0.08)
1985-2010	**0.1146**	(0.05)	**0.2076**	(0.00)	(0.04)	**0.2773**	(0.00)	(0.05)	0.3226	(0.00)	(0.12)	0.3269	(0.00)	(0.29)
RBAS Adjusted EY														
Whole Sample	**0.0919**	(0.03)	**0.1333**	(0.00)	(0.07)									
1960-1985	**0.1655**	(0.01)	**0.2310**	(0.00)	(0.04)									
1985-2010	**0.1480**	(0.01)	**0.2511**	(0.00)	(0.01)									

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Table 5.10 Correlation Analysis of Candidate Variable in Entire Sample and Sub-Samples

24- Month Earnings Growth												
Whole Sample							**-0.2628**	(0.00)	(0.07)	**-0.3749**	(0.00)	(0.08)
1960-1985							-0.2113	(0.00)	(0.35)	-0.2278	(0.00)	(0.53)
1985-2010							-0.3214	(0.00)	(0.12)	**-0.5670**	(0.00)	(0.05)
90 Day Overbought/Sold												
Whole Sample	0.0947	(0.02)										
1960-1985	0.1329	(0.02)										
1985-2010	0.0488	(0.40)										
5-Year Overbought/Sold												
Whole Sample				-0.2029	(0.00)	(0.06)	-0.3054	(0.00)	(0.04)	-0.4382	(0.00)	(0.04)
1960-1985				-0.1711	(0.01)	(0.30)	-0.2560	(0.00)	(0.29)	-0.4373	(0.00)	(0.25)
1985-2010				-0.2725	(0.00)	(0.05)	-0.4128	(0.00)	(0.04)	-0.5169	(0.00)	(0.08)

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Table 5.10 Correlation Analysis of Candidate Variable in Entire Sample and Sub-Samples

1- Month Historic Returns	Correlation	P-Value	Correlation	P-Value	Adjusted P-Value	Correlation	P-Value	Adjusted P-Value	Correlation	P-Value	Adjusted P-Value	Correlation	P-Value	Adjusted P-Value
Whole Sample	**0.1028**	(0.01)												
1960-1985	**0.1608**	(0.01)												
1985-2010	0.0364	(0.53)												
36- Month Historic Returns														
Whole Sample									**-0.3041**	(0.00)	(0.04)	**-0.4259**	(0.00)	(0.04)
1960-1985									-0.3005	(0.00)	(0.19)	-0.4700	(0.00)	(0.18)
1985-2010									**-0.3553**	(0.00)	(0.08)	-0.4067	(0.00)	(0.18)

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Table 5.10 Correlation Analysis of Candidate Variable in Entire Sample and Sub-Samples

48- Month Historic Returns								
Whole Sample	**-0.0992**	(0.02)	**-0.1775**	(0.00)	(0.02)	**-0.2424**	(0.00)	(0.02)
1960-1985	-0.1021	(0.11)	**-0.1885**	(0.00)	(0.09)	-0.2455	(0.00)	(0.12)
1985-2010	**-0.1154**	(0.05)	**-0.1941**	(0.00)	(0.05)	**-0.2807**	(0.00)	(0.05)

Bracketed values provide the probability that the correlation between the independent and dependent variable is not significant at the 10% level. Bolded figures indicate that the correlation between variables is significant at the 10% level. OLS Coefficients (adjusted p-values in brackets). All bolded figures are significant at the 10% level. ALSI Sample Period: 1 January 1960 – 31 January 2010. Earnings Yield is measured as EPS/P. RBAS Adjusted Earnings Yield is measured as EY/RBAS. 24-Month Earnings Growth is measured as ln(EPS(t))-ln(EPS(t-24)). % Overbought/Sold is measures as (P_{ALSI}-MA_{ALSI})/MA_{ALSI}. T-period historic returns are calculated as $\ln(ALSI_t)$-$\ln(ALSI_{t-T})$. Adjusted p-value is calculated by adjusting the number of observations in the standard error of the correlation by dividing it by the square root of the length of the return forecast.

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Of the nineteen combinations of candidate and dependent variables, only the correlation between six are significant, at the 10% level, in both sub-samples. These are the three candidate variables for 3-month returns (earnings yield, RBAS adjusted earnings yield and 48-month returns), earnings yield with 1 and 6-month returns and RBAS adjusted earnings yield with 1-month returns. This indicates that, for the remaining relationships, the significance of the candidate variable applies to only one of the sub-samples. However, in certain cases, neither sub-sample period yields a significant correlation, a result that seems somewhat implausible. A comparison of the correlation values in the differing sample periods shows that, in most cases, these values are not substantially different and are generally higher in the individual sub-samples. Therefore, the decrease in significance has less to do with a change in correlation but more to do with a decrease in the number of observations in each sub-sample.

However, several of the correlations, such as those between the short-term momentum indicators and 1-month returns or earnings growth with long-term returns, are substantially lower in the 1985-2010 sub-sample period relative to the entire sample and the earlier sub-sample, which could indicate that there is a decrease in predictive power of this variable in the second sub-sample.

As this visual comparison of correlations lacks a quantifiable measure to determine unsuitable variances, as well as its inability to note any structural breaks, a more rigorous method is required. One that is both statistically sound and simplistic in nature is to estimate the ordinary least squares relationship between each factor and the respective return timeframe with the inclusion of both a constant and coefficient dummy variable for when the sample is in the second sub-sample (1985-2010). If the coefficient dummy is significant at the 10% level, this indicates that the relationship between the candidate variable and the relevant return timeframe is significantly different in the two sub-samples.

The tables below reports the ordinary least squares regression results of the single-factor predictive variables and its relevant return horizon, including both a dummy intercept and slope coefficient variable to test for a structural break between the two sub-sample periods. Due to the dependent nature of returns greater than 1-month, the p-value related to the adjusted t-statistic is reported, where the adjusted t-statistic is calculated as the t-statistic divided by the square root of the number of months in the return timeframe.

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Table 5.11 OLS Analysis of Sub-Sample Structural Break

	1 Month Returns		3 Month Returns		6 Month Returns		12 Month Returns		24 Month Returns	
Earnings Yield										
Intercept	-0.0136	(0.21)	-0.0429	(0.21)	-0.0705	(0.30)	-0.1312	(0.32)	-0.2966	(0.21)
1985-2010 Intercept Dummy	-0.0056	(0.77)	-0.026	(0.66)	-0.0559	(0.64)	-0.0613	(0.79)	0.1924	(0.65)
Coefficient	**0.1902**	(0.04)	**0.6001**	(0.04)	**1.0938**	(0.06)	**2.1353**	(0.05)	**4.7261**	(0.02)
1985-2010 Coefficient Dummy	0.1976	(0.35)	0.7093	(0.29)	1.3605	(0.31)	1.9825	(0.45)	-0.0738	(0.99)
Adjusted R^2	0.01		0.04		0.07		0.12		0.22	
EY Adjusted RBAS										
Intercept	**-0.0222**	(0.05)	-0.0555	(0.13)						
1985-2010 Intercept Dummy	0.0060	(0.72)	0.0057	(0.91)						
Coefficient	**0.0206**	(0.00)	**0.0542**	(0.02)						
1985-2010 Coefficient Dummy	0.0197	(0.28)	0.0688	(0.23)						
Adjusted R2	0.02		0.05							
24-Month Earnings Growth										
Intercept							**0.1603**	(0.01)	**0.3173**	(0.01)
1985-2010 Intercept Dummy							0.0572	(0.56)	0.1168	(0.51)
Coefficient							-0.2308	(0.27)	-0.4082	(0.28)
1985-2010 Coefficient Dummy							-0.1207	(0.69)	-0.3159	(0.58)
Adjusted R2							0.07		0.15	

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Table 5.11 OLS Analysis of Sub-Sample Structural Break

90-Day Overbought/Sold Indicator								
Intercept	**0.007**	(0.06)						
1985-2010 Intercept Dummy	0.0038	(0.47)						
Coefficient	**0.1684**	(0.02)						
1985-2010 Coefficient Dummy	-0.106	(0.32)						
Adjusted R2	0.01							
5-Year Overbought/Sold Indicator								
Intercept			**0.0766**	(0.03)	**0.1615**	(0.01)	**0.3611**	(0.00)
1985-2010 Intercept Dummy			0.0582	(0.30)	0.1129	(0.30)	0.1153	(0.57)
Coefficient			-0.0892	(0.23)	-0.1908	(0.18)	**-0.4608**	(0.07)
1985-2010 Coefficient Dummy			-0.0832	(0.49)	-0.1704	(0.47)	-0.0796	(0.85)
Adjusted R2			0.05		0.11		0.21	
1-Month Historic Returns								
Intercept	**0.0066**	(0.07)						
1985-2010 Intercept Dummy	0.0045	(0.39)						
Coefficient	**0.1625**	(0.00)						
1985-2010 Coefficient Dummy	-0.1289	(0.11)						
Adjusted R2	0.01							

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Table 5.11 OLS Analysis of Sub-Sample Structural Break

36-Month Historic Returns										
Intercept							**0.1667**	(0.01)	**0.3578**	(0.00)
1985-2010 Intercept Dummy							0.0939	(0.38)	0.0814	(0.68)
Coefficient							-0.1886	(0.11)	**-0.4243**	(0.05)
1985-2010 Coefficient Dummy							-0.1059	(0.61)	0.0163	(0.97)
Adjusted R2							0.10		0.20	
48-Month Historic Returns										
Intercept	**0.0151**	(0.01)	**0.048**	(0.01)	**0.0955**	(0.01)				
1985-2010 Intercept Dummy	0.0114	(0.27)	0.0329	(0.31)	0.0675	(0.30)				
Coefficient	**-0.0164**	(0.09)	**-0.0565**	(0.06)	**-0.1080**	(0.08)				
1985-2010 Coefficient Dummy	-0.0099	(0.55)	-0.0248	(0.64)	-0.0586	(0.58)				
Adjusted R2	0.01		0.03		0.07					

OLS Coefficients (adjusted p-values in brackets). All bolded figures are significant at the 10% level. ALSI Sample Period: 1 January 1960 – 31 January 2010. Earnings Yield is measured as EPS/P. RBAS Adjusted Earnings Yield is measured as EY/RBAS. 24-Month Earnings Growth is measured as ln(EPS(t))-ln(EPS(t-24)). % Overbought/Sold is measures as $(P_{ALSI}-MA_{ALSI})/MA_{ALSI}$. T-period historic returns are calculated as $\ln(ALSI_t)-\ln(ALSI_{t-T})$

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The coefficients between earnings yield and future returns are positive and significant at the 10% level. The coefficient grows at a fairly linear rate and the p-value remains fairly constant as the return timeframe increases. It also grows to have a large impact, with a 1% change in earnings yield leading to a 4.73% change in 24-month returns. The intercept dummy is negative, indicating that returns, controlling for earnings yield, are generally lower after 1985 than before. The coefficient dummy is positive and roughly the same size as the original coefficient, except for the coefficient dummy for 24-month returns, which is negative. This implies that earnings yield has a stronger effect after 1985 for most returns. However, none of the dummies are significant at the 10% level and therefore one can conclude that these results only weakly hold.

The coefficients between earnings yield adjusted for the short-term yield and future returns are positive and significant at the 10% level. There is a close to linear increase in the coefficient from 1 to 3-month returns. Both the intercept dummies and the coefficient dummies are positive, with the coefficient dummies being roughly the same size of the 1960-1985 coefficient This finding implies that the returns, while taking into account the adjusted earnings yield, is slightly higher than before 1985, with the effect of the adjusted earnings yield more pronounced after 1985. However, both of the dummy variables are not significant at the 10% level, so this finding only weakly holds.

The coefficient between earnings growth and 12 and 24-month future returns is negative and increases in an approximately linear fashion. However, the relationship is not significant at the 10% level. The intercept dummy is positive, indicating that post-1985 returns are slightly higher, holding earnings growth constant. However, the coefficient dummy is negative, indicating that earnings growth has a greater effect post-1985. However, neither dummy variable is significant at the 10% level. These findings suggest that, when taking into account the different sub-samples, earnings growth does not have a significant relationship with future returns at the 10% level. To test this thoroughly, the OLS regression is restricted such that both the coefficient and coefficient dummy betas are equal to zero. A f-test is then calculated on the restricted least squares estimation, with an adjusted f-statistic, which is the f-statistic divided by the number of months in the return horizon, used to adjust for the loss of degrees of freedom incurred by using rolling returns.

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Table 5.12 Joint Significance of Earnings Growth Coefficient and Dummy Coefficient with Future Returns

	12-Month Returns	24-Month Returns
F-Statistic	22.28	50.38
Adjusted F-Statistic	6.43	10.28
P-Value	0.00	0.00

F-Statistic calculated as $F = \frac{\left(R_{UR}^2 - R_R^2\right)/m}{\left(1 - R_{UR}^2\right)/\left(n-k\right)}$, where UR relates to the regression where all variables are unrestricted, R relates to the regression where both coefficient variables are jointly restricted to zero, m is the number of restrictions, n is the number of observations in the unrestricted regression and k is the number of parameters in the unrestricted regression (Gujarati, 2003: 268). Adjusted f-statistic is calculated as $\overline{F} = \frac{F}{\sqrt{r}}$, where r is the number of months in the return horizon.

The results above suggest that, although there may not be individual significance when adding a sub-sample dummy, earnings growth and its interaction term are jointly significant with 12 and 24-month returns, and should be included in their multifactor forecast models.

The coefficient on the 90-day overbought/sold indicator is positive and significant at the 10% level. The intercept dummy is marginally positive, implying marginally higher returns, holding the indicator constant, after 1985. The coefficient is negative and quite significantly reduces the effectiveness of the variable in impacting returns, implying that the variable has less of an effect after 1985. However, neither of the dummy variables is significant at the 10% level.

The coefficient for the 5-year overbought indicator is negative, indicating an inverse relationship between the variable and future returns. The coefficient grows at a more than linear rate, indicating that it has a greater effect on future returns as the return horizon increases. However, only the coefficient for 24-month returns is significant at the 10% level. The intercept dummy is positive, indicating that returns, holding the indicator constant, are greater after 1985. The coefficient dummy is negative and almost of the same magnitude for 12-month returns, indicating that the effect strengthens after 1985, whereas it is closer to zero for 24-month returns, indicating that the effect is only marginally different in the two sub-samples. However, none of the dummy

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variables are significant. Although none of the coefficient variables for 6 and 12-month returns is individually significant, they may be jointly significant. The f-test approach for the restricted least squares regression is used to test this joint significance, with the test using an adjusted f-statistic (as above), used to adjust for the loss of degrees of freedom incurred by using rolling returns.

Table 5.13 Joint Significance of the 5-Year Overbought/Sold Indicator Coefficient and Dummy Coefficient with Future Returns

	6-Month Returns	12-Month Returns
F-Statistic	13.03	33.41
Adjusted F-Statistic	5.32	9.65
P-Value	0.01	0.00

F-Statistic calculated as $F = \frac{\left(R_{UR}^2 - R_R^2\right)/m}{\left(1 - R_{UR}^2\right)/(n-k)}$, where UR relates to the regression where all variables are unrestricted, R relates to the regression where both coefficient variables are jointly restricted to zero, m is the number of restrictions, n is the number of observations in the unrestricted regression and k is the number of parameters in the unrestricted regression (Gujarati, 2003: 268). Adjusted f-statistic is calculated as $\overline{F} = \frac{F}{\sqrt{r}}$, where r is the number of months in the return horizon.

It is evident from the table that, although there may not be individual significance when adding a sub-sample dummy, the 5-year overbought/sold indicator and its interaction term are jointly significant with 6 and 12-month returns, and should be included in their multifactor forecast models.

1-month historic returns have a positive relationship with 1-month future returns and are significant at the 10% level. The intercept dummy is marginally positive, indicating a slight increase in mean returns, holding the indicator constant. However, the coefficient dummy is negative and reduces the magnitude of the coefficient dramatically, suggesting that the indicator does not have as large an effect after 1985. However, neither of the dummy variables is significant at the 10% level.

The coefficient for 36-month historic returns is negative for all timeframes and its magnitude increases greater than linearly with the return horizon. However, only the coefficient for 24-month returns is significant at the

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10% level. The intercept dummy is constantly positive while the coefficient is negative, indicating that mean returns are initially higher but return reversal is stronger after 1985. However, none of the dummy variables are significant at the 10% level. Although neither the 12-month coefficient nor its coefficient dummy is significant at the 10% level, they can only be removed from the analysis if they jointly are not significant. To test this, a f-test of the restricted least squares estimation is performed, and the results are tabulated below. Like the previous uses of this test, an adjusted f-statistic is used to adjust for the loss of degrees of freedom incurred by using rolling returns.

Table 5.14 Joint Significance of 36-Month Historic Returns Coefficient and Dummy Coefficient with Future Returns

	12-Month Returns
F-Statistic	32.73
Adjusted F-Statistic	9.45
P-Value	0.00

F-Statistic calculated as $F = \frac{\left(R_{UR}^2 - R_R^2\right)/m}{\left(1 - R_{UR}^2\right)/\left(n-k\right)}$, where UR relates to the regression where all variables are unrestricted, R relates to the regression where both coefficient variables are jointly restricted to zero, m is the number of restrictions, n is the number of observations in the unrestricted regression and k is the number of parameters in the unrestricted regression (Gujarati, 2003: 268). Adjusted f-statistic is calculated as $\overline{F} = \frac{F}{\sqrt{r}}$, where r is the number of months in the return horizon.

The results of the restricted f-test indicate that 36-month historic returns and its dummy coefficient should be used in the later analysis of a 12-month multifactor forecast model.

The 48-month historic return coefficient is negative for all timeframes and its magnitude increases fairly linearly with the return horizon. The coefficients are also significant at the 10% level. The intercept dummy is constantly positive while the coefficient dummy is negative, indicating that, returns start off higher and the return reversal effect is larger after 1985. However, none of the dummy variables are significant at the 10% level.

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Summary of Sub-Sample Analysis Ordinary Least Squares Regressions

An initial analysis of correlations and their probabilities in the two sub-samples suggests that there may be differences in the predictive relationship between candidate variables and their respective return timeframes in the two sub-samples. To more rigorously test this, a regression analysis with a dummy for a structural break is performed. The inclusion of the dummy variables to test for structural breaks yields some interesting results. With the exception of earnings yield, the intercept dummy is positive, implying that, holding the predictor variable constant, there are higher returns after 1985. However, none of the intercept dummies are significant at the 10% level. There is no clear-cut pattern in the coefficient dummy, with certain variables having a larger (in absolute terms) coefficient after 1985 and the reverse occurring in others. Again, like the intercept dummies, none of the coefficient dummy variables are significant at the 10% level. The inclusion of the structural break dummy variables also reduces the individual significance of certain variables below 10%; however, there is still a joint significance of all coefficient and the coefficient interaction dummy variables at the 10% level.

5.2.4 Correlations between Independent Variables

Correlation between dependent variables can lead to multicollinearity, which can impact on inference testing. As the multifactor models that are the focus of this study are predictive, this problem is less troublesome than if the models were designed to be inferential in nature. However, too great a correlation can lead to an inability to estimate ordinary least squares regression models due to near-perfect multicollinearity. One could also reduce variables to make a more parsimonious model, as suggested by Occam's Razor (Gujarati, 2003). The table below reports the correlations between all dependent variables.

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Table 5.15 Correlations of Independent Variables

	Earnings Yield	RBAS Adjusted Earnings Yield	24-Month Earnings Growth	90-Day Overbought/Sold Indicator	5-Year Overbought/Sold Indicator	1-Month Historic Returns	36-Month Historic Returns	48-Month Historic Returns
Earnings Yield	1							
RBAS Adjusted Earnings Yield	0.5684	1						
24-Month Earnings Growth	0.2341	0.2143	1					
90-Day Overbought/Sold Indicator	0.0225	0.1027	0.2066	1				
5-Year Overbought/Sold Indicator	-0.2307	-0.0267	0.4579	0.2944	1			
1-Month Historic Returns	0.0697	0.1056	0.2334	**0.9014**	0.2186	1		
36-Month Historic Returns	-0.1915	-0.0512	0.4969	0.1775	**0.8869**	0.1357	1	
48-Month Historic Returns	-0.1362	-0.1635	0.4532	0.1092	**0.8232**	0.0812	**0.7874**	1

Correlations of dependent variables. All bolded figures have correlations greater than 0.7.

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The table above indicates that the majority of independent variables are not highly correlated with one another. Only the correlation between 1-month historic returns and the 90-day overbought/sold indicator has a correlation above 0.9 at 0.9014. Other correlations that warrant concern are those of 36-month historic returns and 48-month historic returns with 5-year historic returns, which are 0.8869 and 0.8232 respectively. The correlation between 36-month and 48-month historic returns is also, as expected, fairly high, at 0.7874. However, these two variables are never included in the same return timeframe regression and therefore will not lead to precarious multicollinearity directly.

The high correlation between historic returns and the overbought/sold indicator is of concern, as these variables are included simultaneously in some form in the multifactor forecast models for all but 3-month return timeframes. But these variables also provide the strongest relationships with future returns, and their exclusion will lead to a decrease in predictive power. As this study focuses on the prediction and exploitation of JSE returns, the loss of inferential quality due to multicollinearity is less of a concern relative to predictive power. As there is no sign that there is perfect multicollinearity (which will lead to a complete methodological failure), all candidate variables will be included in their respective multifactor forecast models.

5.2.5 Conclusion

A detailed analysis of potential independent variables for inclusion in multifactor forecast models is undertaken above. The visual analysis confirms a relationship between the ALSI and most of the candidate variables, with the volatility in short-term independent variables preventing any clear visual relationship to be found. The results of the unit root tests find that all returns and candidate variables have no unit root, significant at the 10% level, implying that these variables are stationary. A single-factor regression analysis with the candidate variable and its relevant future return, including a structural break, finds limited evidence of a structural break for the sample period before 1985 and after 1985, but the structural break dummy variables are not significant at the 10% level, indicating that no mid-sample break exists. Finally, the analysis of correlations between candidate independent variables finds certain instances of high correlation between variables. However, as these do not fall dangerously close to perfect multicollinearity, the focus on predictive power must take priority over the loss of inferential quality, and therefore, no variables are excluded.

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To conclude, all candidate variables are analysed to ensure fitness for inclusion in multifactor forecast models. All candidate variables are found to meet the criteria required for inclusion.

5.3 Cointegrating Relationship on the JSE

Cointegration between a set of independent variables and a dependent variable creates a superconsistent relationship between the two, and any variations from the relationship will lead to a short-term error correction. The presence of a cointegrating relationship on the JSE ALSI would allow for the inclusion of this residual, a strong predictive variable, in the multifactor forecast models. The methodology provides a rationale to the choice of variables chosen to estimate a cointegrating relationship. Certain criteria are required for a statistically significant cointegrating relationship to exist: firstly, the dependent variable must be non-stationary; the dependent variable side and the exogenous variable side must be matched in order of cointegration (balanced); the residuals must be stationary (Fedderke, 2003: 160); and the coefficient of the long-run residual in the error-correction mechanism (ECM) estimation must be negative (Gujarati, 2003: 825).

Table 5.16 Unit Root Test of the Log of the JSE ALSI

	t-Statistic	p-Value
Log(JSE ALSI)	0.0408	(0.96)

Table of t-Statistics (p-Values in brackets), calculated using the Augmented Dickey Fuller Test with a maximum lag of 10. t-statistic calculated as

$$\Delta Y_t = \beta_0 + \beta_1 t + \delta Y_{t-1} + \sum_{i=1}^{m} \alpha_i \Delta Y_{t-1} + \varepsilon_t$$

Bolded figures are significant (stationary) at the 10% level. ALSI Sample Period: February 1965 – January 2010 (for 1 month results; other results begin 2, 5, 11 & 23 months later respectively). JSE ALSI is the Johannesburg Stock Exchange All Share Index, a market-capitalisation weighted index of all shares on the Johannesburg Stock Exchange. EPS is earnings per share and is the weighted average of the earnings of the shares included in the JSE ALSI. RBAS is the 90-day Bankers Discount Rate. US$/R is the exchange rate between the American Dollar and the South African Rand. The Economist Metal Index is an industrial commodity price index created by The Economist.

The results above indicate that the natural log of the JSE ALSI is not stationary at the 10% level and therefore must be at least an integrated of order one process. 1-month returns, as illustrated above, are stationary, and therefore the natural log of the JSE ALSI cannot be an integrated of order two process. Thus, the natural log of the JSE ALSI is integrated of order one.

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With the order of integration of the dependent variable established, the order of the integration of the candidate independent variables must also be established. The results of the unit-root tests for first-order integration are tabulated below.

Table 5.17 Unit Root Tests of the Log of Independent Variables

	t-Statistic	p-Value
Log(EPS)	-0.0191	(0.96)
Log(RBAS)	**-3.01624**	(0.03)
Log(US$/R)	-0.0655	(0.95)
Log(Economist Metal Index)	-1.4573	(0.55)

Table of t-Statistics (p-Values in brackets), calculated using the Augmented Dickey Fuller Test with a maximum lag of 10. t-statistic calculated as

$$\Delta Y_t = \beta_0 + \beta_1 t + \delta Y_{t-1} + \sum_{i=1}^{m} \alpha_i \Delta Y_{t-1} + \varepsilon_t .$$

Bolded figures are significant (stationary) at the 10% level. ALSI Sample Period: February 1965 – January 2010 (for 1 month results; other results begin 2, 5, 11 & 23 months later respectively). JSE ALSI is the Johannesburg Stock Exchange All Share Index, a market-capitalisation weighted index of all shares on the Johannesburg Stock Exchange. EPS is earnings per share and is the weighted average of the earnings of the shares included in the JSE ALSI. RBAS is the 90-day Bankers Discount Rate. US$/R is the exchange rate between the American Dollar and the South African Rand. The Economist Metal Index is an industrial commodity price index created by The Economist.

The results above indicate that, with the exception of RBAS, all the time series are not stationary at the 10% level, so are at least integrated of order one. RBAS is stationary at the 10% level so it is assumed that it is integrated of order zero. As the remaining three time series may be integrated to order of two, a unit root test of their first differences is calculated. If the first differences are stationary, the time series are integrated of order one and the single-equation estimation will be balanced. If they are not stationary, then the time series are integrated of an order higher than one, and a cointegrating relationship will have to be found between independent variables for the single-equation estimates to be balanced. The results of the unit root tests of the first difference of the log of the non-stationary independent variables are tabulated below.

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Table 5.18 Unit Root Tests of the First Difference of the Log of Independent Variables

	t-Statistic	p-Value
ΔLog(EPS)	**-19.9170**	(0.00)
ΔLog(US$/R)	**-21.2175**	(0.00)
ΔLog(Economist Metal Index)	**-19.3847**	(0.00)

Table of t-Statistics (p-Values in brackets), calculated using the Augmented Dickey Fuller Test with a maximum lag of 10, defined as $\Delta Y_t = \beta_0 + \beta_1 t + \delta Y_{t-1} + \sum_{i=1}^{m} \alpha_i \Delta Y_{t-1} + \varepsilon_t$ (Gujarati, 2003). Bolded figures are significant (stationary) at the 10% level. ALSI Sample Period: February 1965 – January 2010 (for 1 month results; other results begin 2, 5, 11 & 23 months later respectively). JSE ALSI is the Johannesburg Stock Exchange All Share Index, a market-capitalisation weighted index of all shares on the Johannesburg Stock Exchange. EPS is earnings per share and is the weighted average of the earnings of the shares included in the JSE ALSI. RBAS is the 90-day Bankers Discount Rate. US$/R is the exchange rate between the American Dollar and the South African Rand. The Economist Metal Index is an industrial commodity price index created by The Economist.

The remaining time series variables are stationary at the 10% level. As such, this study concludes that the natural log of EPS, US$/R and the Economist Metal Index are processes that are integrated of order one. As a result, the two sides of the single-equation cointegrating estimation are balanced and a long-run cointegrating relationship can be estimated. The results of this are tabulated below.

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Table 5.19 Cointegration Regression Results

Variable	Log(JSE ALSI)	
Intercept	**2.1422**	(0.00)
Log(EPS)	**0.4361**	(0.00)
Log(RBAS)	**-0.1846**	(0.00)
Log(US$/R)	**0.9200**	(0.00)
Log(Economist Metal Index)	**0.4342**	(0.00)
Adjusted R^2	0.98	

OLS Coefficients (p-values in brackets). All bolded figures are significant at the 10% level. ALSI Sample Period: February 1965 – January 2010 (for 1 month results; other results begin 2, 5, 11 & 23 months later respectively). JSE ALSI is the Johannesburg Stock Exchange All Share Index, a market-capitalisation weighted index of all shares on the Johannesburg Stock Exchange. EPS is earnings per share and is the weighted average of the earnings of the shares included in the JSE ALSI. RBAS is the 90-day Bankers Discount Rate. US$/R is the exchange rate between the American Dollar and the South African Rand. The Economist Metal Index is an industrial commodity price index created by The Economist.

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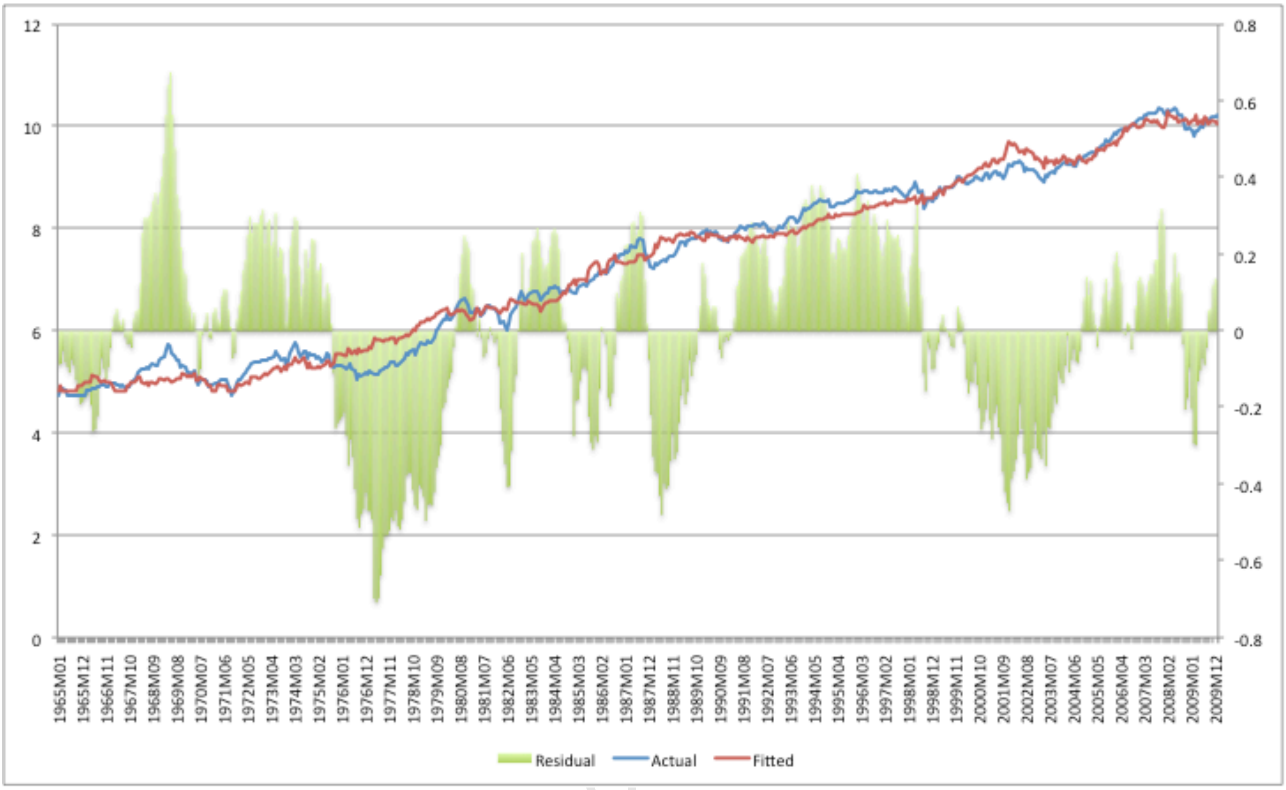
The results from the cointegrating ordinary-least squares regression indicate that there are strong relationships between the selected variables and the ALSI. The exchange rate almost moves one-for-one with the ALSI, with a 1% change in the exchange rate leading to a 0.92% change in the ALSI. Earnings per share and the Economist metal index move less proportionately, with a 1% change in these variables leading to a roughly 0.435% change in the ALSI. The discount rate has an inverse relationship, with a 1% change in it leading to a 0.18% change in the ALSI in the opposite direction. A graph of the fitted, actual and residual of the cointegrating relationship is provided for visual analysis.

Figure 5.13 Cointegrating Relationship with the JSE ALSI



It is clear that there are long swings from the fair value suggested by the regression model above. However, these deviations tend to reverse over time, indicating that swings away from fundamental value are reversed in the long term. However, these results can only be considered significant if the residuals of this regression model are stationary. The results of the augmented Engle and Granger Test on the residuals are tabulated below.

Table 5.20 Augmented Engle & Granger Test of Residual

	t-Statistic	Engle & Granger Critical Value (1% Level)
Residual	**-3.8750**	-2.5899

Table of t-Statistics calculated using the Augmented Dickey Fuller Test with a maximum lag of 10. Bolded figures are significant (stationary) at the 1% level. Augmented Engle & Granger test defined as $\Delta Y_t = \beta_0 + \beta_1 t + \delta Y_{t-1} + \sum_{i=1}^{m} \alpha_i \Delta Y_{t-1} + \varepsilon_t$ (Gujarati, 2003). Engle & Granger Critical Value found in Gujarati (2003: 823).

The augmented Engle and Granger Test on the residual rejects the null hypothesis of a unit-root at the 1% level, and therefore one concludes that the residual is stationary. The final requirement is that the residual of the coefficients of the long-run are negative in the ECM mechanism. The ECM is defined as:

$\Delta y_t = \beta_0 + \sum_{i=1}^{k} B_i \Delta x_{i,t} + \delta z_{t-1} + u_t$, where y is the dependent variable, k are the number of independent variables in the long-run relationship, x_i is the i^{th} explanatory variable and z is the error term from the long-run relationship (Gujarati, 2008). The estimation of the ECM is presented below.

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Table 5.21 OLS Estimation of the Error-Correction Mechanism

Variable	ΔLog(JSE ALSI)$_t$	
Intercept	**0.0055**	(0.01)
ΔLog(EPS)$_t$	**0.4644**	(0.00)
ΔLog(RBAS)$_t$	**-0.1752**	(0.00)
ΔLog(US$/R)$_t$	-0.0514	(0.36)
ΔLog(Economist Metal Index)$_t$	**0.1552**	(0.00)
Long-Run Residual$_{t-1}$	**-0.0166**	(0.04)
Adjusted R^2	0.51	

OLS Coefficients (p-values in brackets). All bolded figures are significant at the 10% level. ALSI Sample Period: February 1965 – January 2010 (for 1 month results; other results begin 2, 5, 11 & 23 months later respectively). JSE ALSI is the Johannesburg Stock Exchange All Share Index, a market-capitalisation weighted index of all shares on the Johannesburg Stock Exchange. EPS is earnings per share and is the weighted average of the earnings of the shares included in the JSE ALSI. RBAS is the 90-day Bankers Discount Rate. US$/R is the exchange rate between the American Dollar and the South African Rand. The Economist Metal Index is an industrial commodity price index created by The Economist. Long-Run Residual is the error term in the regression estimated in Table 5.3.2.

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The coefficients for the variables in the ECM, with the exception of the currency variable, are significant at the 10% level and predict slightly over 52% of short-term variation. Most importantly, the coefficient of the long-run residual is significantly negative at the 10% level. Thus, the requirements for cointegration are met and the residual can be included in the multifactor forecast models.

Although the variable meets the statistical requirements, the tests above do not indicate that there is a significant relationship between the error-correcting residual and future returns. An ordinary least squares regression between the error-correcting residual and the varying future returns is presented below, including the structural break dummies.

Table 5.22 OLS Regressions between Residual and Future Returns

	1 Month Returns		3 Month Returns		6 Month Returns		12 Month Returns		24 Month Returns	
Intercept	**0.0072**	(0.08)	**0.0209**	(0.10)	**0.0439**	(0.09)	**0.0927**	(0.05)	**0.2011**	(0.02)
Coefficient	**-0.0398**	(0.01)	**-0.1303**	(0.01)	**-0.2578**	(0.01)	**-0.5183**	(0.00)	**-0.9930**	(0.00)
1985-2010 Intercept Dummy	0.0051	(0.36)	0.0159	(0.36)	0.0279	(0.42)	0.0471	(0.47)	0.0684	(0.55)
1985-2010 Coefficient Dummy	0.0033	(0.89)	0.0123	(0.86)	0.0476	(0.74)	0.1378	(0.61)	0.6414	(0.17)
Adjusted R^2	0.02		0.06		0.11		0.22		0.35	

OLS Coefficients (adjusted p-values in brackets). All bolded figures are significant at the 10% level. ALSI Sample Period: 1 January 1960 – 31 January 2010. The residual is calculated as the difference between the actual log of the ALSI and the predicted log of the ALSI according to the OLS cointegrating regression tabulated in table 4.3.2.

All the coefficients are negative and significant at the 10% level. The coefficients are consistently negative, indicating that any movements away from the long-run equilibrium will be corrected in future months. The coefficients grow in a fairly linear manner, with 24-month returns almost having a one-for-one relationship with the residual. The intercept dummy is consistently positive, indicating that returns are greater after 1985, holding the residual constant. The coefficient dummy is positive, thereby indicating that the residual has a smaller effect post-1985. However, both structural break dummies are not significant at the 10% level, and therefore this finding has only limited significance.

It is noticeable that the adjusted R^2 of the residual regression on returns is substantially higher than the strongest candidate variable. For 1 and 3-month returns, the adjusted R^2 is roughly double that of the strongest relevant return timeframe candidate predictor, while for 6-24 month returns, although not quite double, the increase in predictive power is still substantial. This implies that the residual from the cointegrating relationship is a relatively strong predictor of future returns compared to the previous candidate predictors.

As there are significant relationships between the cointegrating regression residual and all return timeframes, this variable should also be included in all return timeframes' multifactor forecast models.

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6 Results: Multifactor Forecast Model

This chapter is broken up into two sub-sections. In 6.1, multifactor regressive models are estimated for each of the relevant return time horizons using the relevant significant variables found in chapter 5 and their forecasting power analysed. In 6.2, the forecasts from these models are applied to three trading strategies and their performance compared to that of a pure buy-and-hold strategy of the JSE ALSI.

6.1 Return Forecast Models

The initial multifactor models estimated are those attempting to predict the JSE ALSI Return, using the candidate variables for each return horizon as well as the cointegrating residual as independent variables. Due to no variable having a significant structural break, no structural break dummy variables are included in the analysis. To determine whether the models have overall significance, an adjusted f-statistic is utilised, where the traditional f-statistic of joint significance of all included variables is divided by the square root of the number of months in the relevant return horizon. These results are tabulated below.

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Table 6.1 Summary of Multifactor OLS Estimation of JSE Returns

	1 Month Returns		3 Month Returns		6 Month Returns		12 Month Returns		24 Month Returns	
Intercept	0.00826	(0.44)	0.0491	(0.14)	0.0991	(0.13)	**0.1912**	(0.09)	0.2679	(0.15)
Cointegration Residual	**-0.03448**	(0.04)	**-0.1086**	(0.04)	**-0.2123**	(0.04)	**-0.5539**	(0.00)	**-0.7101**	(0.02)
Earnings Yield	-0.12216	(0.28)	-0.0940	(0.79)	-0.0561	(0.93)	0.0586	(0.96)	1.5239	(0.41)
RBAS Adjusted EY	0.00914	(0.13)	0.0056	(0.76)						
24-Month Earnings Growth							**-0.4403**	(0.01)	**-0.8051**	(0.01)
90-Day Overbought/Sold	0.08446	(0.51)								
5 Year Overbought/Sold					0.0578	(0.57)	0.1106	(0.61)	0.0792	(0.82)
1-Month Returns	0.03434	(0.73)								
36-Month Returns							-0.0212	(0.91)	-0.0049	(0.99)
48-Month Returns	-0.01162	(0.17)	-0.0320	(0.22)	-0.1073	(0.21)				
Adjusted R^2	0.03		0.07		0.12		0.32		0.52	
Overall Model Adjusted F-Statistic	**3.5751**	(0.00)	**5.9966**	(0.00)	**8.0439**	(0.00)	**14.9383**	(0.00)	**23.4746**	(0.00)

OLS Coefficients (adjusted p-values in brackets). All bolded figures are significant at the 10% level. ALSI Sample Period: 1 January 1960 – 31 January 2010. Earnings Yield is measured as EPS/P. RBAS Adjusted Earnings Yield is measured as EY/RBAS. % Overbought/Sold is measures as $(P_{ALSI}\text{-}MA_{ALSI})/MA_{ALSI}$. T-period historic returns are calculated as $\ln(ALSI_t)\text{-}\ln(ALSI_{t\text{-}T})$. Cointegration residual is calculated as the difference between the actual log of the ALSI and the predicted log of the ALSI according to the OLS cointegrating regression tabulated in table 5.3.2. Adjusted f-statistic is calculated as original f-statistic divided by the length of the return horizon, such that $\overline{F} = \frac{F}{M}$. All independent variables are lagged by the length of the dependent variable return horizon..

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This table must be interpreted with caution. Due to the high level of potential multicollinearity between the various predictors that are chosen, the coefficients can vary wildly from return timeframe to return timeframe. However, it is evident that the significance of individual variables is generally weak. Despite the weak individual significance of the variables, the f-statistics of overall significance are significant at the 10% level, even after adjusting for return dependency.

The residual from the long-run cointegrating fair value of the ALSI is significant, at the 10% level, and negative for all return time frames. It is the only variable that is significant for all return horizons and this suggests that the cointegrating relationship is a good estimate of ALSI fair value, with any deviations from this fair value correcting over the following time periods, holding other factors constant. The magnitude of the coefficient is also relatively small, indicating that this correction to fair value may take several months to years, which is why it is still significant for returns two-years after the deviation.

The only other variable that is individually significant, at the 10% level, is 24-month earnings growth with 12 and 24-month returns. The coefficients on these relationships are negative, indicating that strong earnings growth in the previous two years leads to worse share return performance for the succeeding one to two years, holding other factors constant. This is an interesting result, as prior performance would suggest a growing economy. However, due to the cyclical nature of the economy, the earnings growth relationship may be picking up turns in the economy, with supernormal earnings growth occurring in boom periods, which are followed by subnormal earnings growth in the following bust periods.

Earnings yield have weak relationships with one-month returns (with a p-values of 0.28), but earnings related variables only have very weak relationships with return timeframes longer than a month. The coefficient between earnings yield and returns is negative for one to six month return timeframes and then positive thereafter (albeit at a highly insignificant level) for 12-month returns. The negative relationships between earnings yield and future returns are interesting, as the OLS sub-sample analysis (section 5.2.3) finds earnings yield to have a continuously positive relationship with returns. The only conclusion that can be drawn is that other variables that are correlated with earnings yield bias the coefficient estimate in a single-factor analysis, and as the multi-factor analysis contains more variables, this leads to less biased estimates for earnings. If this is correct, then lower

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earnings yields lead to higher returns and vice versa, which implies that short-term returns are affected by market confidence, as low earnings yields occur when the market is over-valued and high earnings yields when the market is under-valued.

Adjusted earnings yield has a weak relationship with one-month returns (with a p-value of 0.13) and a very weak relationship with 3-month returns (with a p-value of 0.76). The coefficient remains positive for both return timeframes, which is consistent with its single-factor coefficient. This reinforces the concept that the implicit market return relative to the risk-free rate is directly related to short-term return performance (albeit very weakly for 3-month returns).

Long-term historic returns are weakly related to 1-6 month returns (p-values of 0.17, 0.22 and 0.21 respectively) with coefficients that are consistently negative. This suggests that there tends to be a long-term price reversion effect that is evident in short-term returns. The strength of the relationship weakens substantially for 12 and 24-month returns, but the coefficient remains negative, indicating that, if historic returns do effect these return horizons, the effect follows the trend of a price-reversion.

Short-term momentum variables are very weakly related to one-month returns. They are positive, consistent with the literature suggesting that very short-term returns display evidence of momentum. However, with the inclusion of two momentum variables (90-day overbought/sold indicator and one-month historic returns), there is multicollinearity, which would lead to results that indicate lower relationship strength.

Long-term overbought/sold indicators are very weakly significant with their relevant return timeframes, but it is concerning that their coefficients are positive. This is contrary to the single-factor OLS analysis performed earlier. The only conclusion that can be drawn is that these variables are a proxy for an array of other individual factors and the multifactor OLS analysis has included these variables, estimating an unbiased coefficient for the relationship.

Overall, the results of the multifactor OLS estimation indicates that the strength of correlation of certain variables may have been due to their correlation with certain other strong variables. Once these variables are controlled for, the predictive power of these certain variables drops substantially. Of more interest than the

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inferential results that can be drawn from these results is the performance of the various models in predicting returns. The easiest measure to test the strength of the forecasts is an OLS estimation of the predicted returns against the actual returns. A model with perfect predictive power would have a constant of zero, a coefficient of one and a R^2 of 100. If the coefficient and the constant are statistically significantly different from one and zero respectively, it is indicative of forecast bias. The results of this OLS estimation are below, with the p-value of the betas differing from the perfect case in brackets, along with a graph of the scatter of actual and predicted returns and the regression line.

Table 6.2 OLS Estimation of Predicted versus Actual Returns

	Intercept		Slope		R^2
1-Month Retuns	**0.0097**	(0.00)	**0.0326**	(0.00)	0.03
3-Month Returns	**0.0278**	(0.00)	**0.0723**	(0.00)	0.07
6-Month Returns	**0.0523**	(0.00)	**0.1295**	(0.00)	0.13
12-Month Returns	**0.0801**	(0.00)	**0.3310**	(0.00)	0.33
24-Month Returns	**0.1154**	(0.00)	**0.5295**	(0.00)	0.53

OLS Coefficients (p-value of individual significant difference from 0 for intercept, 1 for slope) and R^2

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Figure 6.1 1-Month Predicted versus Actual Returns

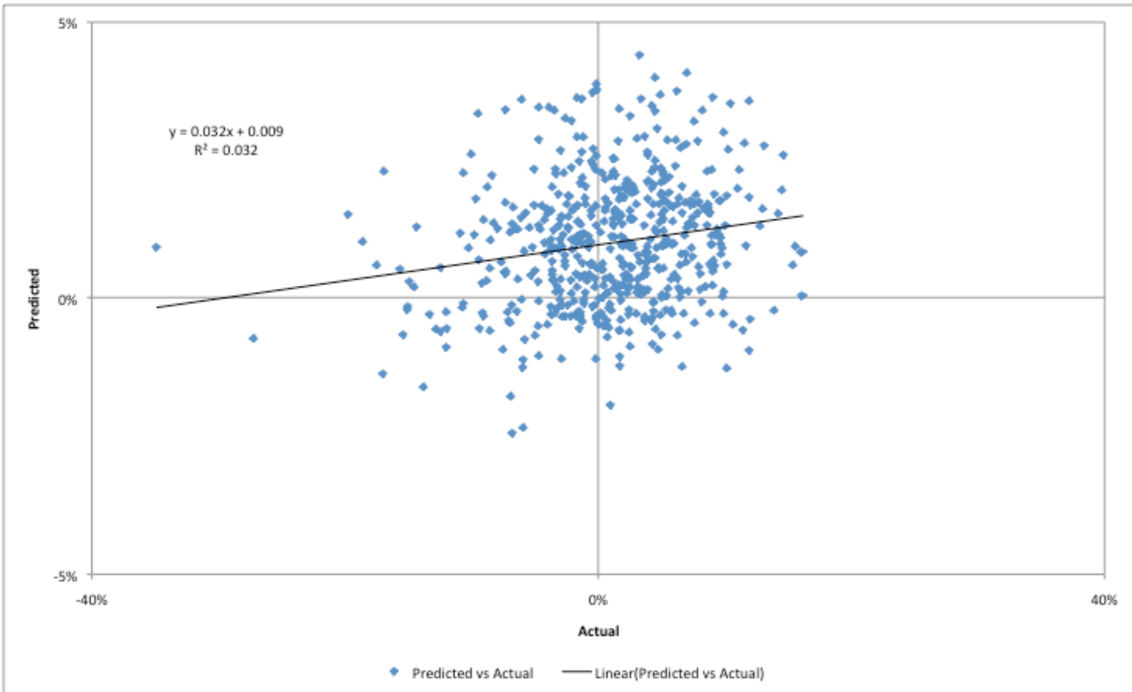


Figure 6.2 3-Month Predicted versus Actual Returns

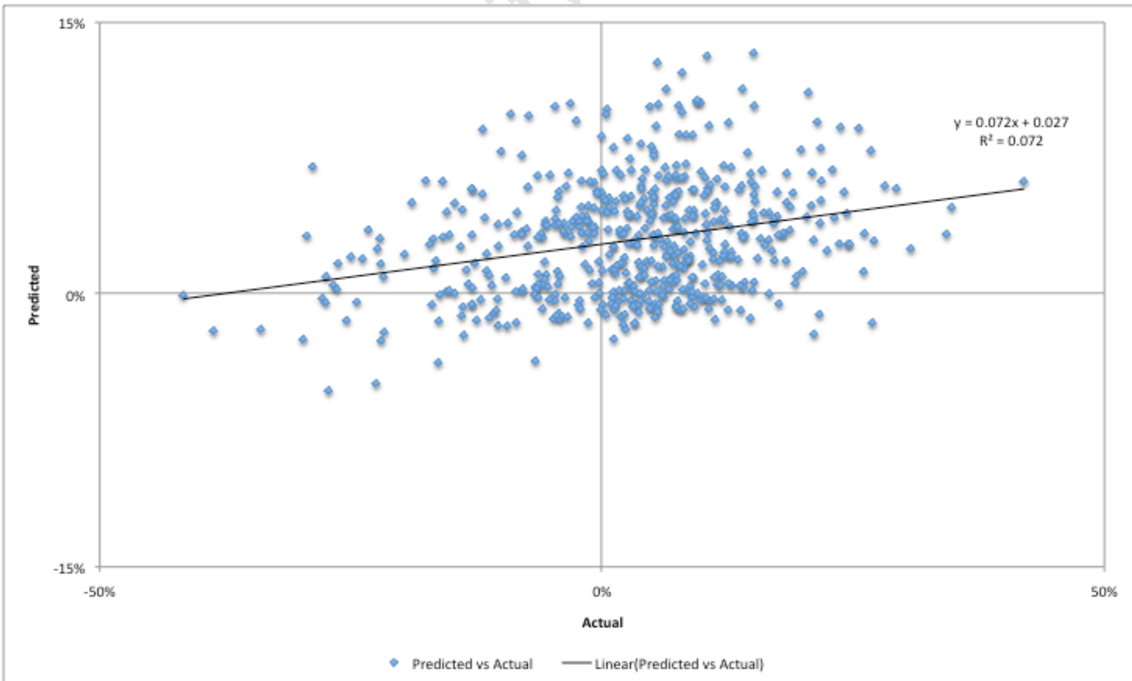


Figure 6.3 6-Month Predicted versus Actual Returns

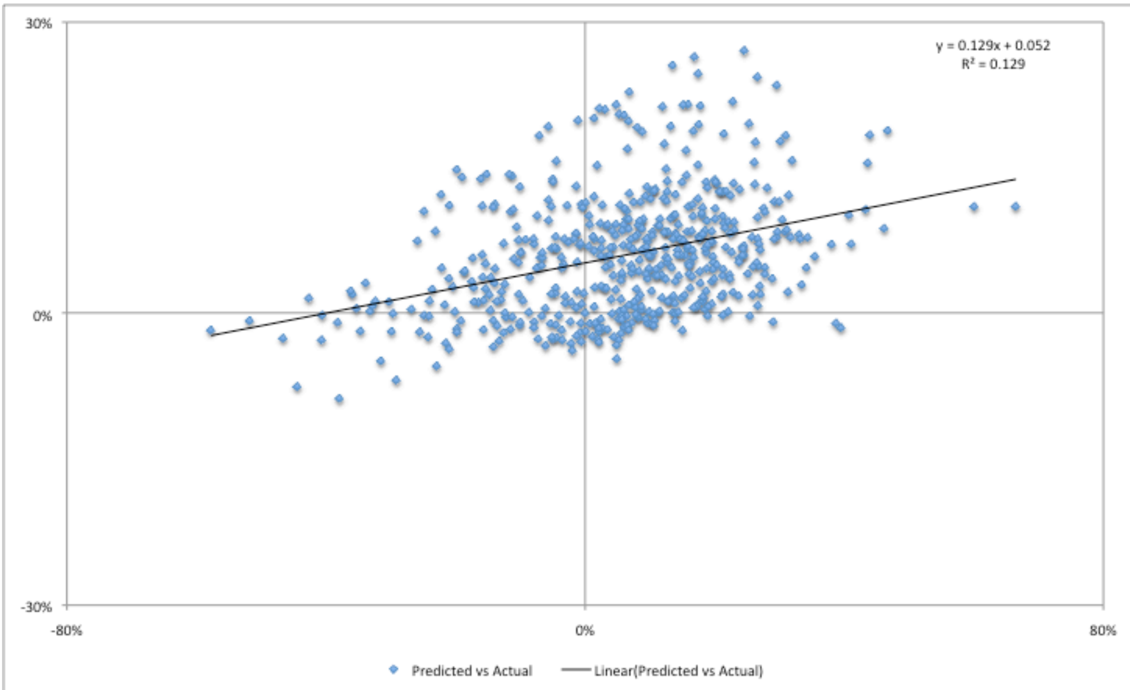


Figure 6.4 12-Month Predicted versus Actual Returns

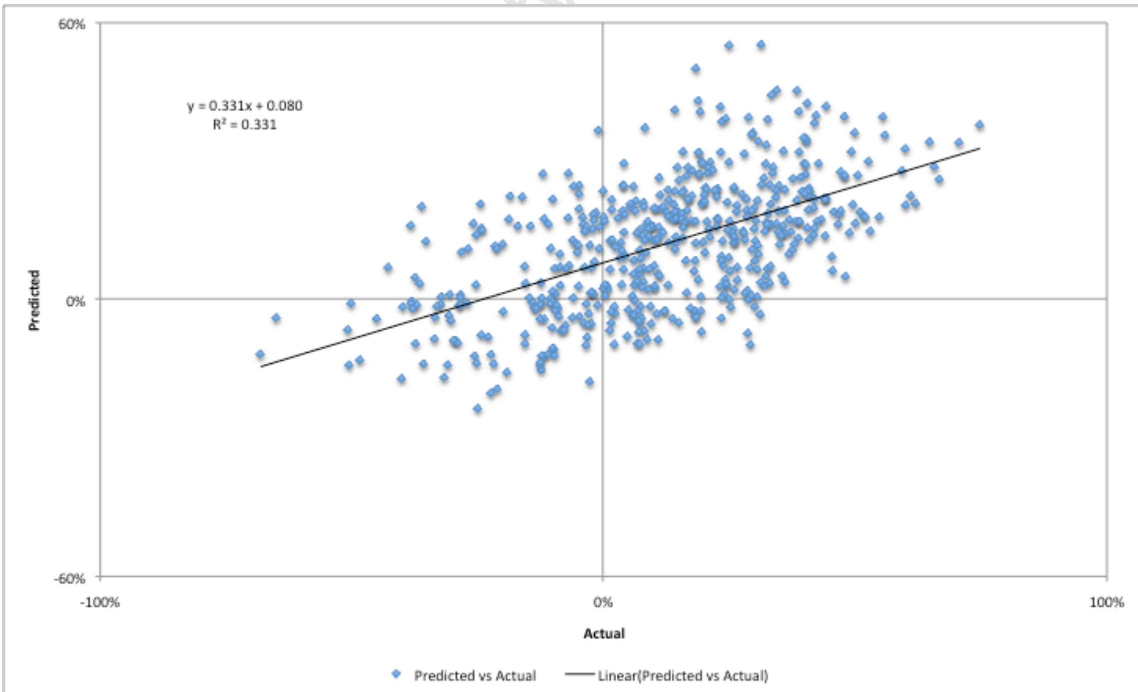
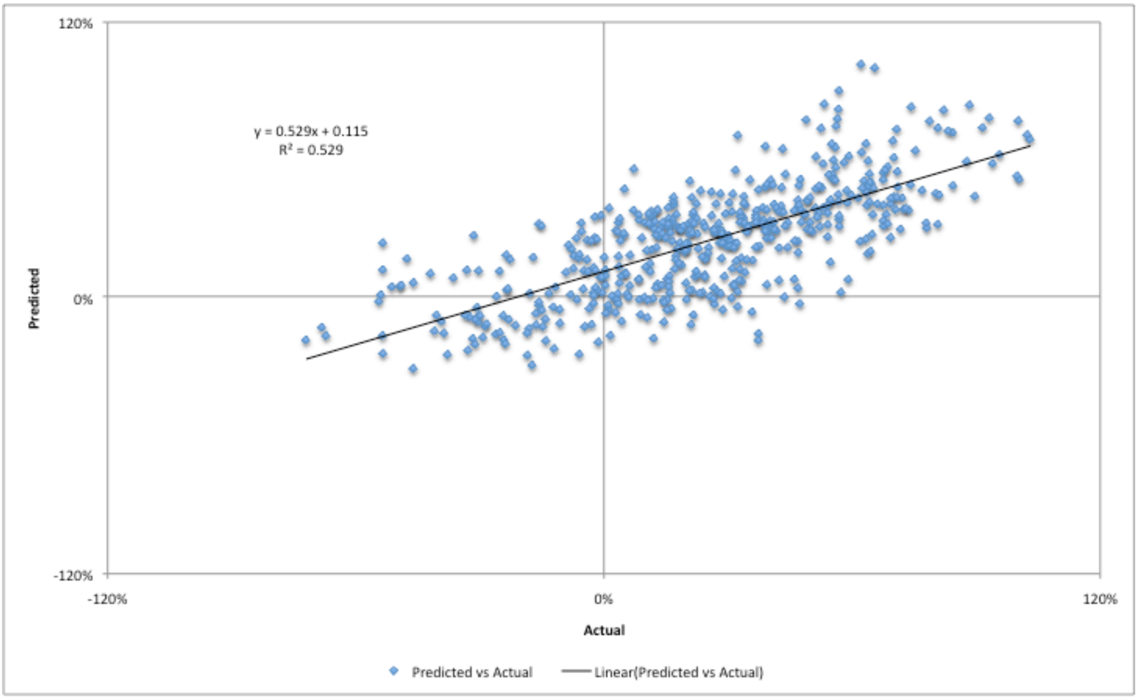


Figure 6.5 24-Month Predicted versus Actual Returns



It is clear from the table above that the relationship between predicted and actual returns is statistically significantly different, at the 1% level, from the perfect case. The intercept across return horizons is consistently positive and the slope is consistently less than one. Finally, the R^2 across return horizons are lower than expected. Longer return horizons tend to have a stronger correlation with predicted returns, possibly due to less noise in the long-run or because of dependency in the returns, but even for 24-month returns, predicted returns only explain 52% of actual return variation. These findings, coupled with a visual analysis of the scatter plots, provide evidence to draw three conclusions.

The first is that, for small returns, the forecasts of the model are consistently higher than the actual returns realised. This is especially problematic because this can change the direction of returns from negative to positive, leading to an incorrect view of the direction of the market. The second conclusion is that the forecasts fall in a narrower range relative to actual returns (due to the slope coefficient being less than one). When returns are more extreme, the forecast model tends to underestimate the magnitude of the direction. However, unlike the first conclusion, this is less problematic, because, in general, the prediction still retains the correct direction of

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return performance. The final conclusion is that the multifactor forecast models, despite the addition of as many significant variables that are significant at the 10% level, are still not providing highly accurate forecasts.

However, predicting the precise magnitude of a return, especially for short-term return horizons, is a near impossible task. A more effective measure of return performance could be to measure the ability of the model to accurately forecast the direction of ALSI returns over the next return horizon. To measure this, a hit-rate is used. The hit-rate is defined as the number of times a positive actual return follows a positive prediction and a negative actual return follows a negative prediction as a percentage of the total forecasts made. However, because the JSE ALSI tends to trend upwards over the long-term, comparing the hit-rate with a benchmark of 50% will overstate the performance of the forecast models (especially for long-term return horizons). Therefore, a benchmark hit-rate is constructed using the incidence of positive return performance as a percentage of all returns observed on the ALSI.

The forecast models and benchmark hit-rates of the various return horizons are reported below.

Table 6.3 Hit-Rate of Forecasts

Return Horizon	Forecast model	Benchmark
1-Month Returns	60.37%	61.85%
3-Month Returns	65.24%	69.52%
6-Month Returns	70.28%	72.15%
12-Month Returns	77.50%	75.80%
24-Month Returns	82.98%	85.88%

Benchmark calculated as hit-rate of a pure buy-and-hold strategy on the JSE ALSI

The hit-rates of the forecast model are lower than the benchmark across all return horizons except for 12-month returns. The hit-rate is less than 2% lower for 1 and 6-month returns, but substantially lower for 3-month returns (over 4%) and 24-month returns (just under 3%). This indicates that, with the exception of 12-month, the model forecasts the direction of JSE ALSI returns less accurately than a model that assumes consistent positive returns. However, the hit-rate does not factor in the impact of an incorrect return direction call. Thus, if the model incorrectly forecasts the directions of returns that are small in absolute magnitude but correctly forecasts the direction of returns that are large in magnitude, it will provide superior returns to a pure buy-and-hold strategy.

6.2 Performance of Forecasts Applied to Trading Strategies

To take this into account, trading strategies are constructed, and their performance metrics compared with the JSE ALSI. However, as these variables are estimating actual JSE return performance and not excess return performance, the risk-free rate (with the RBAS used as a proxy) at the beginning of the month that the predictive decision is to be tested needs to be subtracted from the forecasts. This provides an estimate of the actual excess return expected to be realised. This prediction is then transformed into a probability of outperformance using a normal distribution with a standard error equal to the standard error of the regression. This then provides a percentage probability of an outperformance occurring. This probability is then used in three trading strategies based on the work by Andersen (1996).

To test performance, the annualised average geometric returns, standard deviations, risk-adjusted returns (measured as annualised average geometric return/annualised standard deviation), Jensen's alpha and the portfolio return beta with the ALSI will be used as performance metrics and compared to the JSE ALSI. Years of over, under and identical performance will also be presented, as well as the average percentage held in cash. Finally, the trading strategies will be compared to determine the one with superior performance.

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The first trading strategy (Trading Strategy A) is either wholly invested in the JSE ALSI or the risk-free alternative, based on whether a positive or negative excess return expected. Thus, if the probability of an excess return is greater than 50%, the theoretical investor holds only the JSE ALSI. If the probability is less than 50%, the theoretical investor holds only a short-term cash instrument (with the RBAS used as a proxy in this study).

However, the performance of the first trading strategy is dependent only on the position of the probability of outperformance relative to an arbitrary cut-off, and does not take into account the strength of the signal. To overcome this, the second strategy (Trading Strategy B) invests a percentage of a hypothetical portfolio into the JSE ALSI, with the percentage equalling the probability of outperformance, and the remainder into a risk-free asset. Therefore, p is invested in the ALSI and (100-p) is invested in a risk-free asset, where p is the probability of outperformance.

But, as the second strategy only allows for long positions in two assets, it may also limit potential performance as it prevents the investor from realising any returns that would occur if there is a decline in the JSE ALSI. To expand the second strategy to include this, the third trading strategy (Trading Strategy C) allocates 2p – 100% in stocks. Thus if p=100%, the entire portfolio is taking a long position in the JSE ALSI, while if p=0%, the entire portfolio is taking a short position in the JSE ALSI. The weighting in the risk-free asset is dependent on whether a long or short position is being taken. If a long position is being taken, then the investment in a risk-free asset declines. However, if a short position is being taken, cash is being generated which can then be invested in the risk-free asset. This implies that an investor can hold more than 100% in the risk-free asset. Therefore, the portfolio weighting in the risk-free asset is (200-2p)%.

To implement strategies longer than one-month, it is assumed that the investor breaks up their investment into x equal portions, where x is the length of the return horizon, and invests each portion for the full length of the forecasts return horizon at time t.

The table below summarises the three trading strategy rules.

Table 6.4 Trading Strategy Rules

	Trading Strategy A	Trading Strategy B	Trading Strategy C
JSE ALSI	100% if p > 50%; 0% if p <= 50%	p%	(2p – 100)%
RBAS	0% if p > 50%; 100% if p <= 50%	(100-p)%	(200 – 2p)%

P is the forecasted probability that the JSE ALSI will yield a positive return over the relevant holding period.

To implement strategies longer than one-month, it is assumed that the investor breaks up their investment into x equal portions, where x is the length of the return horizon, and invests each portion for the full length of the forecasts return horizon at time t. The performance metrics of these trading strategies relative to a pure buy-and-hold strategy in the JSE ALSI are reported below.

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Table 6.5 Performance of Trading Strategies relative to the JSE ALSI

		Trading Strategy A	Trading Strategy B	Trading Strategy C	JSE ALSI
1-Month	Average Annualised Return	20.78%	16.13%	13.27%	17.55%
	Annualised Standard Deviation	14.96%	11.03%	3.48%	22.02%
	Risk-Adjusted Return	1.39	1.46	3.81	0.8
	Average % Cash	47.04%	49.31%	98.62%	0%
	Annualised Jensen's Alpha	6.22%	1.30%	2.62%	0%
	Calendar Years Outperformance	19	21	18	
	Calendar Years Underperformance	14	23	26	
	Calendar Years Same Performance	11	0	0	
3-Month	Average Annualised Return	21.26%	16.83%	14.51%	17.49%
	Annualised Standard Deviation	17.26%	12.32%	5.80%	23.92%
	Risk-Adjusted Return	1.23	1.37	2.5	0.73
	Average % Cash	47.77%	48.97%	97.94%	0%
	Annualised Jensen's Alpha	6.30%	1.84%	3.71%	0%
	Calendar Years Outperformance	20	23	22	
	Calendar Years Underperformance	13	21	22	
	Calendar Years Same Performance	11	0	0	
6-Month	Average Annualised Return	21.58%	17.51%	15.80%	17.45%
	Annualised Standard Deviation	18.57%	13.66%	8.40%	25.34%
	Risk-Adjusted Return	1.16	1.28	1.88	0.69
	Average % Cash	47.10%	48.74%	97.48%	0%
	Annualised Jensen's Alpha	6.47%	2.38%	4.79%	0%
	Calendar Years Outperformance	16	20	17	
	Calendar Years Underperformance	17	24	27	
	Calendar Years Same Performance	11	0	0	

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Table 6.5 Performance of Trading Strategies relative to the JSE ALSI

12-Month	Average Annualised Return	21.82%	19.05%	19.36%	17.24%
	Annualised Standard Deviation	21.31%	17.31%	14.32%	26.74%
	Risk-Adjusted Return	1.02	1.10	1.35	0.64
	Average % Cash	46.12%	48.26%	96.53%	0%
	Annualised Jensen's Alpha	6.24%	3.63%	7.26%	0%
	Calendar Years Outperformance	20	20	20	
	Calendar Years Underperformance	12	24	24	
	Calendar Years Same Performance	12	0	0	
24-Month	Average Annualised Return	20.20%	18.90%	19.65%	17.20%
	Annualised Standard Deviation	25.98%	24.02%	22.44%	30.26%
	Risk-Adjusted Return	0.78	0.79	0.88	0.57
	Average % Cash	45.26%	47.44%	94.89%	0%
	Annualised Jensen's Alpha	4.35%	3.06%	6.03%	0%
	Calendar Years Outperformance	18	18	18	
	Calendar Years Underperformance	12	25	25	
	Calendar Years Same Performance	13	0	0	

Sample Period: January 1965 – January 2010. Average Annualised Returns are calculated as (1 + average t-period returns over the sample period) ^ 12/t - 1. The Annualised Standard Deviations are calculated as the standard deviation of returns over the sample period multiplied by the square root of 12/t. The Risk-Adjusted Returns are calculated as average annualised return/annualised standard deviation. Annualised Jensen's alpha is calculated as the annualised C in the regression equation: Excess Returns(Trading Strategy) = C + Beta(Excess Returns(JSE ALSI))

Trading Strategy A

The choice of optimal return timeframe is dependent on the performance metric used. The timeframe with the greatest annualised return is 12-month returns (21.82%), which also has the tied highest number of calendar years where the trading strategy outperforms the JSE ALSI (20) with 3-month returns and the fewest (tied with 24-month returns) calendar years of underperformance (12). However, 1-month returns provide the lowest volatility of returns (14.96%) and the highest risk-adjusted return ratio (1.39). 6-month returns have the highest

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annualised Jensen's alpha (6.47%). These varying results suggest that there are different risk-reward characteristics for the different return timeframes that trading strategy A is applied to.

However, across return timeframes, the trading strategy based on the probabilities derived from the forecast models generally provide superior performance, irrespective of metric chosen, than the JSE ALSI. The absolute returns are always more than 1.5% above the ALSI, with 12-month returns realising returns of 3.28% in excess of the ALSI. Standard deviation of returns range from slightly more than 5% below the standard deviation of the JSE ALSI to 7.06% less than the JSE ALSI for 1-month returns. Risk-adjusted return ratios are consistently higher than the JSE ALSI and all the trading strategies have positive Jensen's alphas, indicating that the trading strategies outperform the ALSI on a risk-adjusted basis consistently, irrespective of holding period.

There is also a trend for less cash to be held as the return timeframe increases. This occurs because of the increased likelihood of earning a positive return on the JSE ALSI increases as an investor increases the holding period, which leads to higher probability of forecasted outperformance being generated from the forecast model.

To analyse the characteristic of returns through time, the cumulative performance of the trading strategy applied to 1-month returns, chosen as it has the best overall risk-reward characteristics, and 12-month returns, chosen as it has the best absolute return characteristics, are graphed against the cumulative performance of the ALSI, based to 100 and using a logarithmic axis scale.

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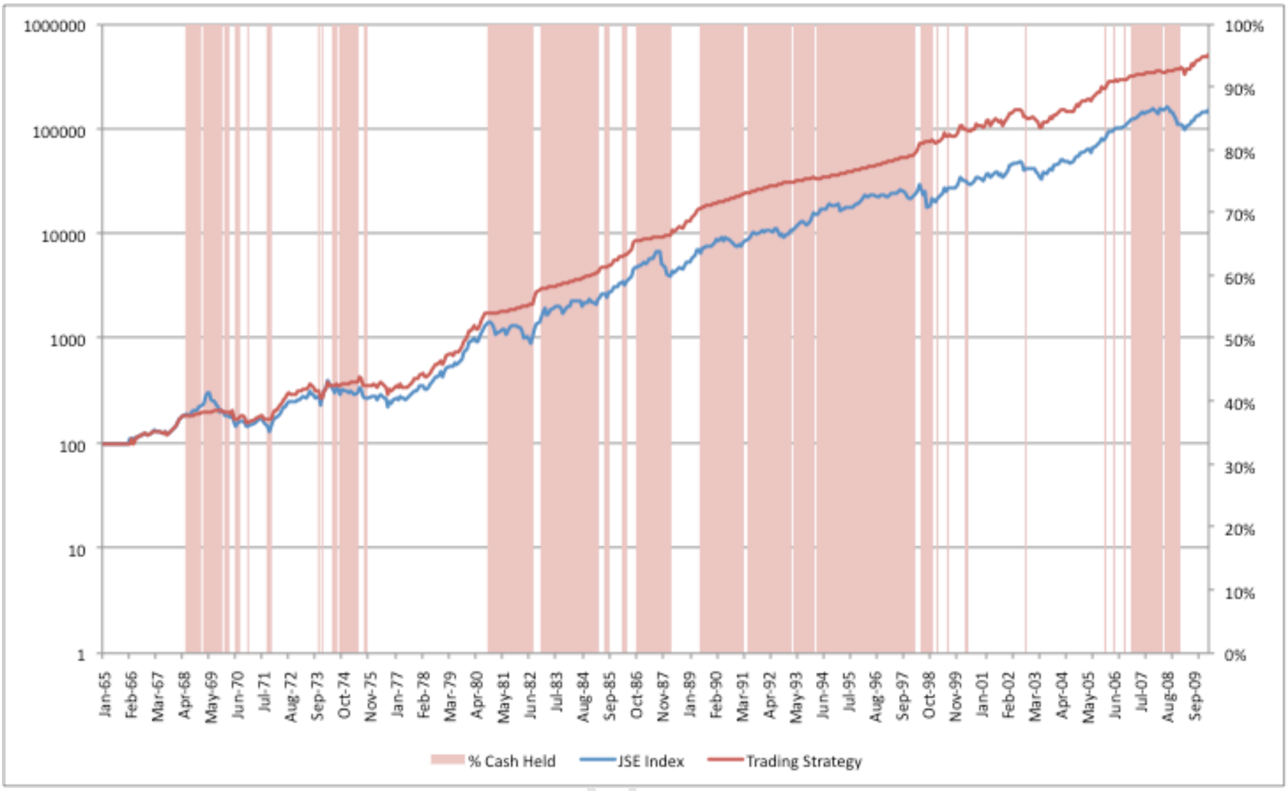
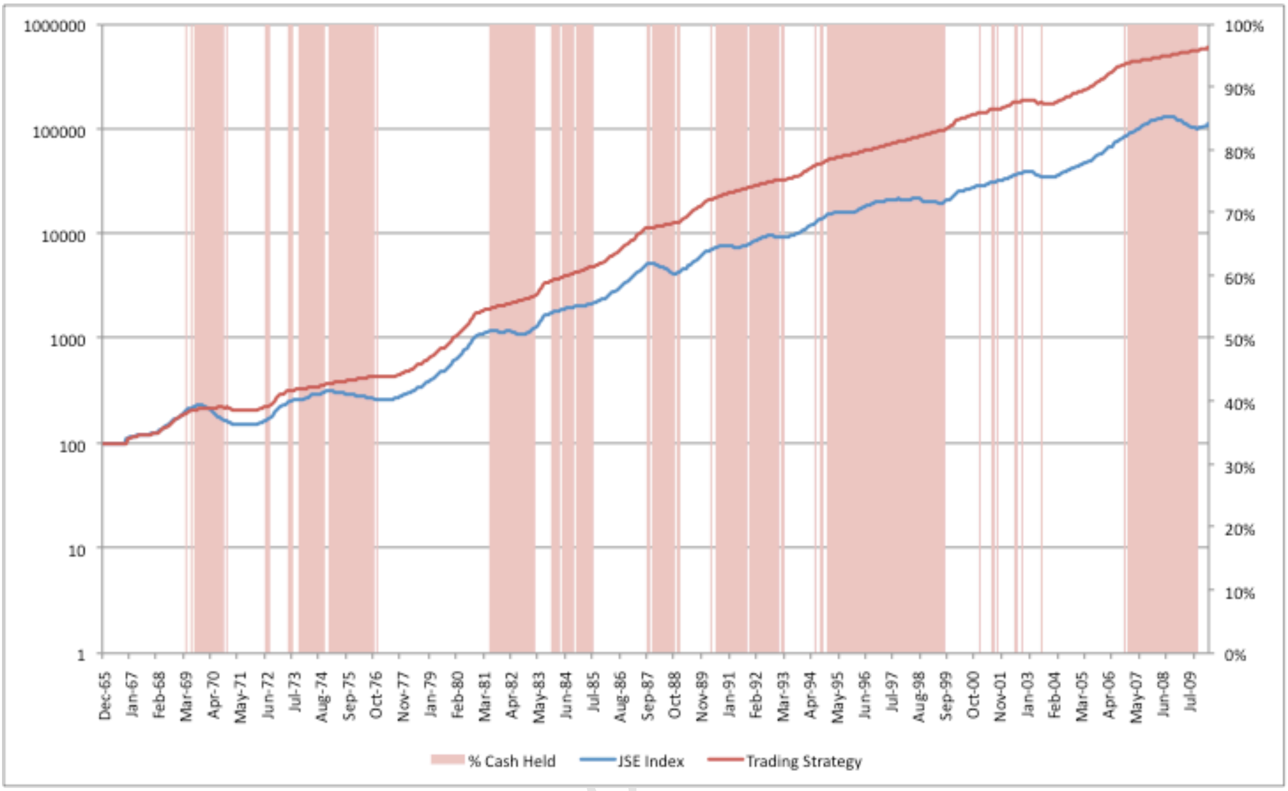
Figure 6.6 Cumulative Value of 1-Month Trading Strategy A relative to the JSE ALSI



A graphical analysis of the trading strategy for 1-month returns shows a smoother, more consistent pattern of returns relative to the ALSI. Although the JSE ALSI initially keeps track and, for a few periods in 1968-1969, has a higher value than the trading strategy, this quickly reverts as the JSE experiences several negative shocks (notably the crash in 1971). The strategy then holds cash for most of the period between 1980-1987, avoiding several sharp declines while still realising several of the sharp increases. Between 1990 and 1998, the strategy once again is generally invested in cash, narrowing the difference between the index value of the ALSI and the trading strategy. For the next 10 years, the trading strategy is generally invested in the ALSI and follows the same pattern, leading to the sharp negative returns that occurred due to the technology bubble crash and the currency crisis of the early 2000s. At the end of the sub-prime bubble, the strategy disinvests from the ALSI and moved into cash, which lead to a non-realisation of the last of the boom returns. However, this movement also leads to the strategy avoiding the severe losses that occur during the sub-prime crisis.

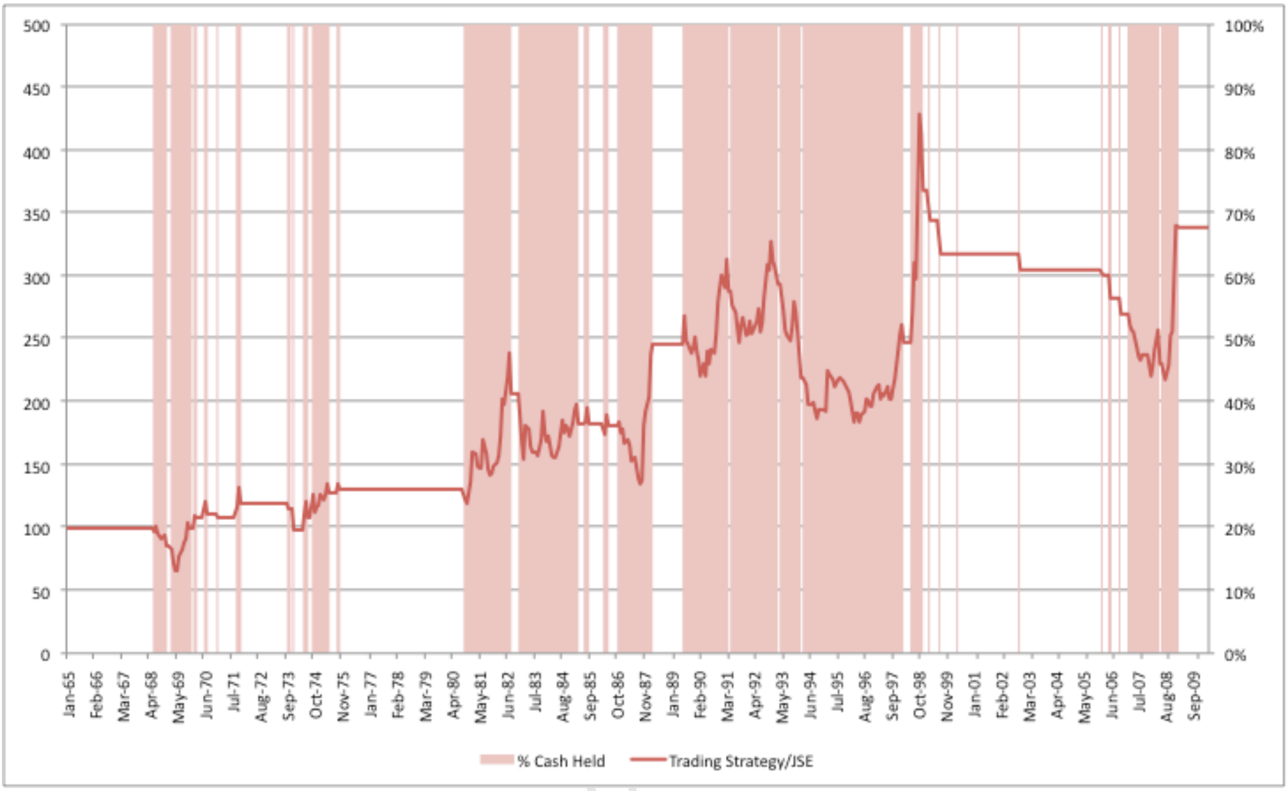
Figure 6.7 Cumulative Value of 12-Month Trading Strategy A relative to the JSE ALSI



Due to the longer return holding period, the returns for both the JSE and the 12-month trading strategy A are smoother than over a 1-month holding period. The periods where cash is held in lieu of the JSE ALSI occur in roughly the same periods as the periods where cash is held for a 1-month holding period, allowing the strategy to avoid negative market returns in the early 1970s, early 1980s, late 1990s and late 2000s. However, unlike 1-month returns, the JSE ALSI is held until early 1969, mid-1987 and between 1993-1995, allowing the hypothetical portfolio to realise those superior returns that occurred in the JSE ALSI in those time periods.

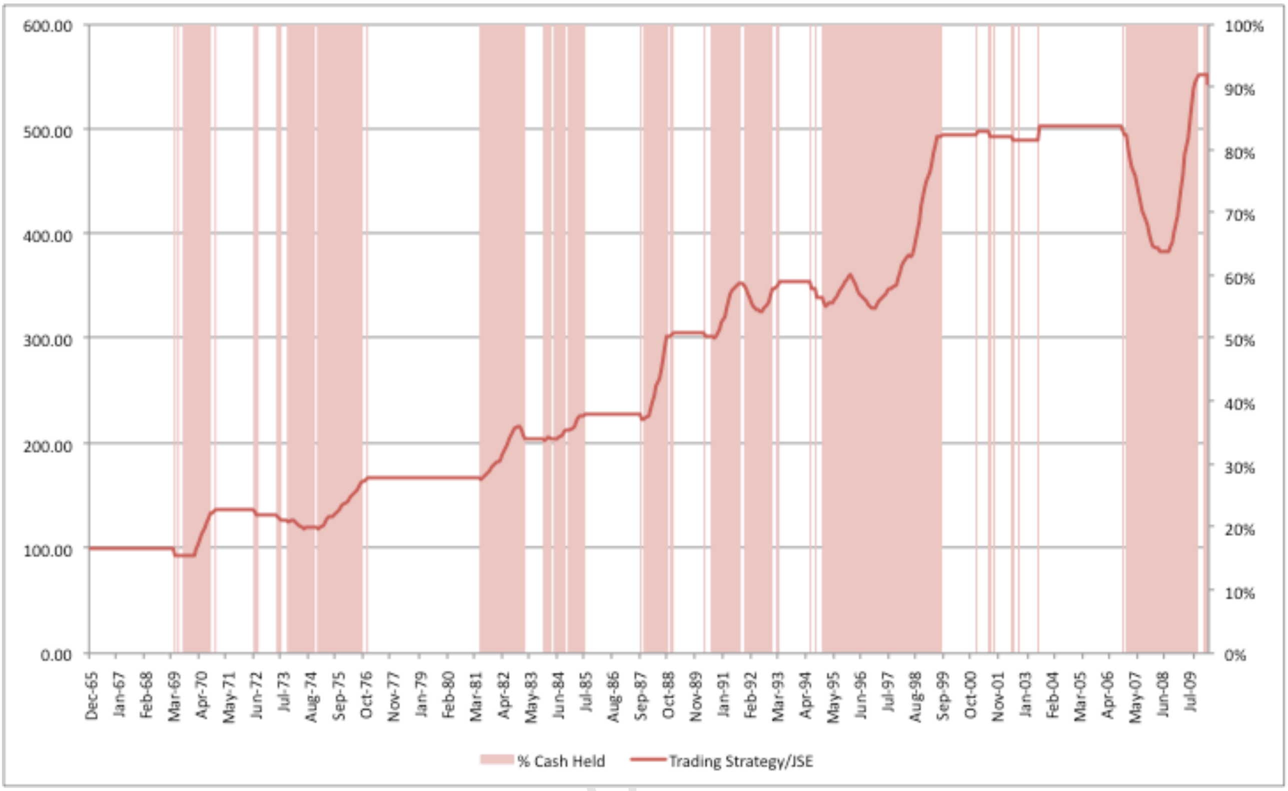
An analysis of indices provides a visual aid to determine periods of positive and negative returns, but to more accurately compare relative performance, the graphs below illustrate the value of the cumulative strategy values relative to the cumulative ALSI value.

Figure 6.8 Cumulative Outperformance of 1-Month Trading Strategy A relative to the JSE ALSI



An analysis of the graph above provides two findings. The first is that the movements, both positive and negative, that the trading strategy experiences relative to the JSE ALSI tend to be large sudden movements and not stable trends. The second is that when the trading strategy moves to cash, there tends to be several periods of underperformance followed by sharp outperformance relative to the JSE ALSI. This suggests that the forecast model is predicting a market decline or crash several periods earlier than the actual crash, moving the investment from the risky ALSI to the risk-free alternative, resulting in the above finding. This leads to an initial underperformance as the bull-run or bubble reaches its peak, before an outperformance, as the market declines sharply while the strategy is invested in a low-yielding but stable asset.

Figure 6.9 Cumulative Outperformance of 12-Month Trading Strategy A relative to the JSE ALSI



Like a 1-month holding period, the outperformance relative to the JSE ALSI generated in the 12-month holding period occurs when the strategy switches from the JSE ALSI to a risk-free cash asset when there is a market decline or crash. But, with one exception occurring in the sub-prime credit generated bubble of 2006-2007, the longer holding period switches out closer to the period where the decline occurs. Therefore, it has fewer periods of underperformance compared to a 1-month holding period, allowing it to generate the greatest average return over the sample period. However, because it is invested more often in the JSE ALSI, it will have a greater variation in returns and therefore higher risk.

In summary, trading strategy A generates outperformance by successful switching assets from the risky JSE ALSI to a cash risk-free asset during periods where the JSE ALSI generates negative returns. Although the choice of return horizon does not seem to affect the generation of this outperformance, it does affect the amount of underperformance that occurs prior to these outperformances, with a 12-month holding period providing the best timing signal.

Trading Strategy B

Like the first trading strategy, the return horizon that provides the best performance is dependent on the metric of performance chosen. 12-month returns yields the highest absolute performance (19.05%) and the highest market risk adjusted returns (annualised Jensen's alpha of 3.63%). 3-month returns has the most calendar years of outperformance (23) and the fewest years of underperformance (21). 1-month returns has the lowest annualised standard deviation (11.03%) and the highest total risk adjusted return (1.46).

Trading Strategy B, like Trading Strategy A, outperforms the JSE ALSI on a risk-adjusted basis, with the outperformance greater than the first trading strategy for total risk adjustment and less for market risk adjustment. This is an intuitive finding: as the second trading strategy will, except for the extreme case when p is 0 or 100, always hold a combination of the two assets, it will therefore create a diversification effect leading to lower total risk (reflected by the lower standard deviations for the second trading strategy). However, because the second trading strategy will again generally be partially invested in the JSE ALSI, it has a higher exposure to the market, leading to a higher beta and a lower Jensen's alpha.

However, in absolute performance, Trading Strategy B underperforms relative to Trading Strategy A. This is most noticeable for 1 and 3-month returns, where underperformance relative to trading strategy A is in excess of 4% and where the strategy yields returns lower than the JSE ALSI. As the return horizon increases, the magnitude of the underperformance relative to Trading Strategy A declines and the strategy outperforms the JSE ALSI. This result could be caused by the cluster of the probability values for 1 and 3-month returns. Because the ALSI is more volatile in shorter timeframes, the predicted excess returns will be closer to zero than for longer return timeframes. This leads to the probabilities of outperformance clustering around 50%. Indeed, for 1 and 3-month returns, the average cash held is more than 2% greater than for the respective portfolio using the rules in Trading Strategy A. Thus, for short-term returns, the rules of this trading strategy restrains any potential outperformance as it forces the hypothetical investor to retain an excess holding of the asset expected to underperform.

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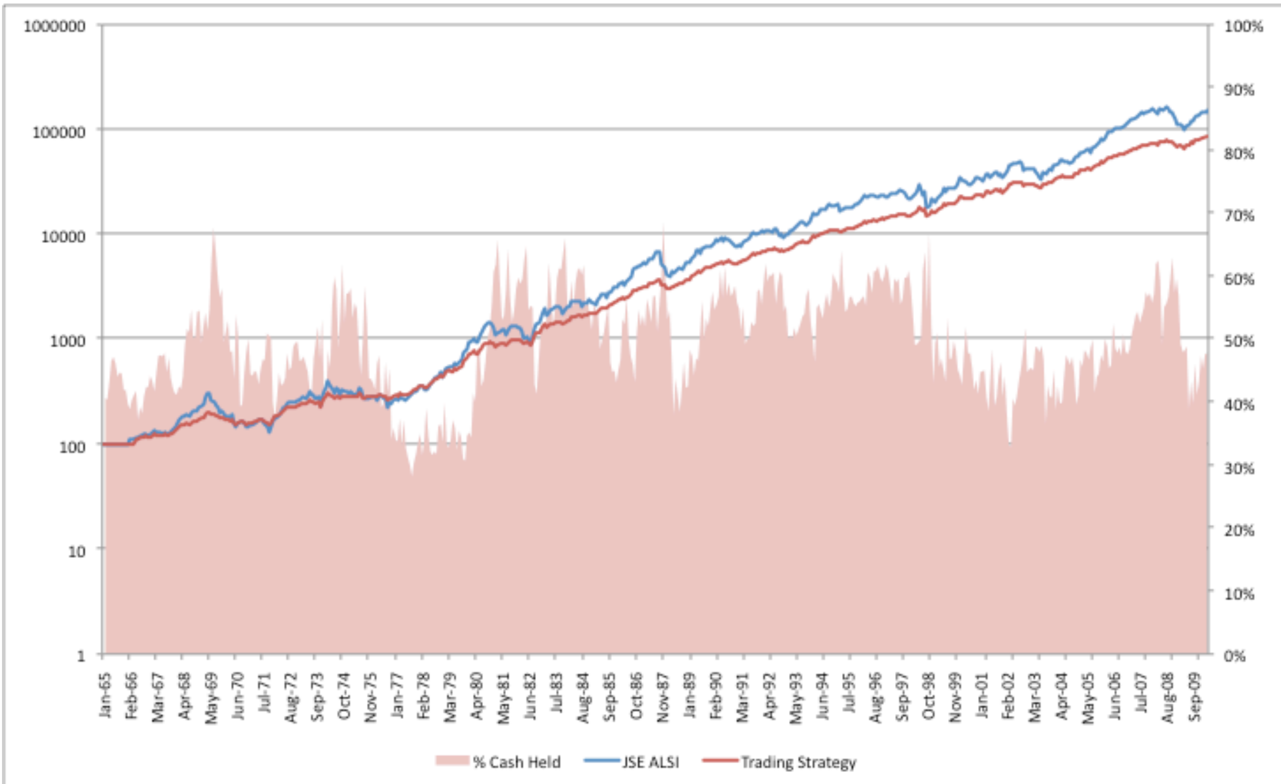
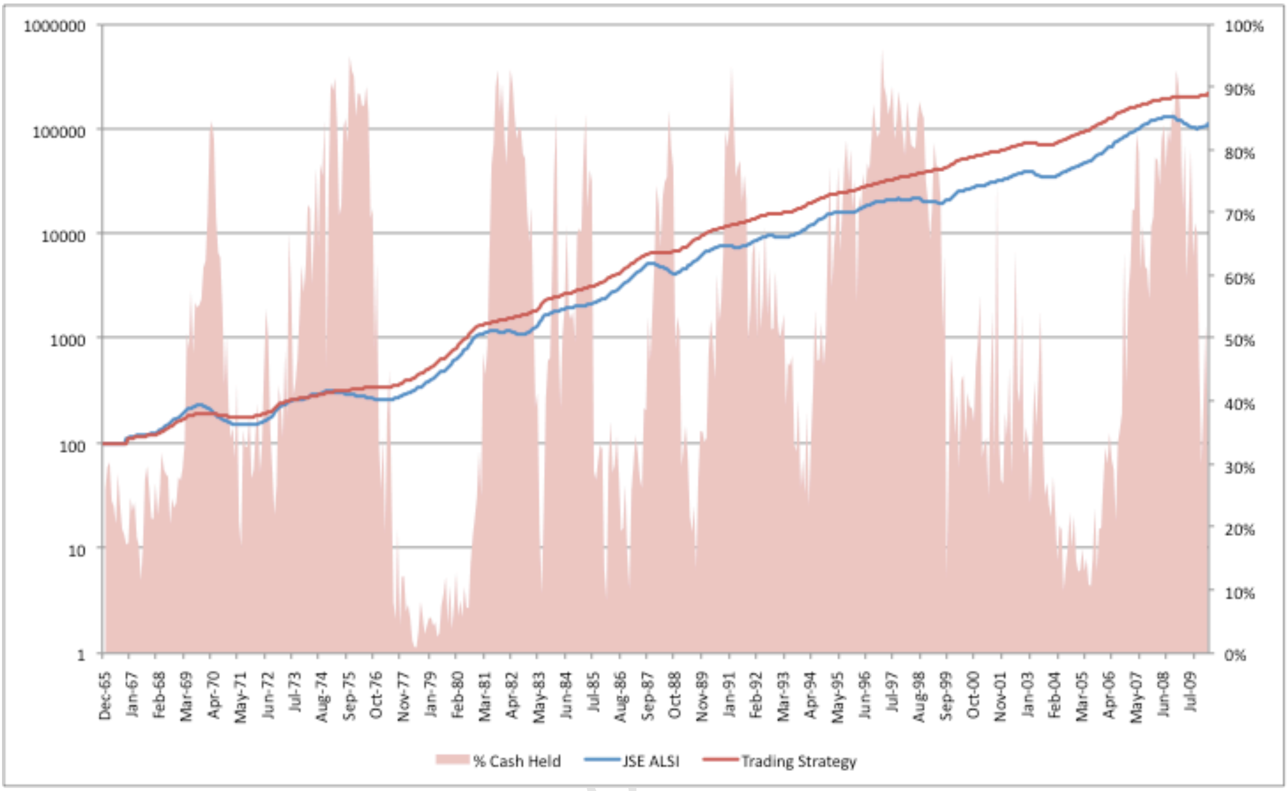
To analyse the characteristic of returns through time, the cumulative performance of trading strategy B applied to 1-month returns, chosen as it has the best overall risk-reward characteristics, and 12-month returns, chosen as it has the best absolute return characteristics, are graphed against the cumulative performance of the ALSI, based to 100 and using a logarithmic axis scale.

Figure 6.10 Cumulative Value of 1-Month Trading Strategy B relative to the JSE ALSI



As explained above, due to the volatile nature of 1-month returns, the probability values of a 1-month positive return are clustered around 50%. Therefore, there are no occasions where less than 30% or significantly more than 70% of the portfolio is held in the JSE ALSI. As a result of this, the portfolio tends to follow the same trend as the JSE ALSI, but with a lower absolute magnitude. Therefore, in upswings, portfolio returns are positive but less positive than the JSE ALSI and during downswings portfolio returns are negative but less negative than the JSE ALSI. As the JSE ALSI has had more upswings than downswings over the sample covered, the portfolio underperforms relative to the JSE ALSI.

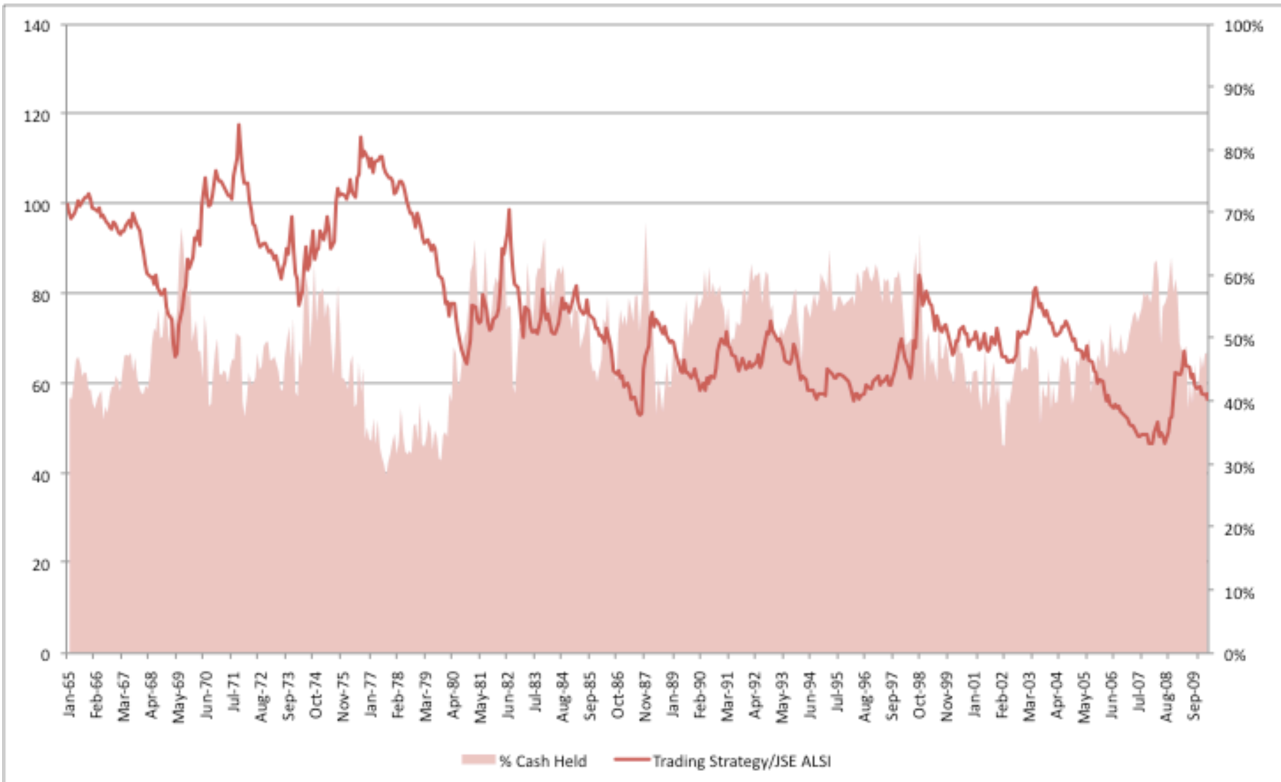
Figure 6.11 Cumulative Value of 12-Month Trading Strategy B relative to the JSE ALSI



Unlike 1-month returns, 12-month returns tend to be bigger in magnitude, therefore creating the variation in the p-values leading to sizeable differences in the weightings of the two asset classes. On several occasions, the cash holding is above 90%, while there is a period between 1976-1981 where the holding in the JSE ALSI is less than 10%. The portfolio also tends to heavily weight one portfolio or the other and there are relatively few occasions where the holdings in the two assets are between 40 and 60%. Like the 1-month portfolio, the 12-month portfolio is also unable to maintain the same returns as the JSE ALSI during an upswing, although this effect is less marked. However, in a downswing, the heavy weightings of the risk-free cash asset during downswings such as at the end of 1970, 1982, early 1988 and during the sub-prime crisis of 2007-2008 leads to a positive return. Thus, this portfolio tends to generate returns similar, albeit lower, to the JSE ALSI during a market upswing and retain that historic performance, and in certain cases, generate additional performance, during a stock market downswing. However, because the portfolio tends to be heavily weighted in individual asset classes, there is less diversification across assets, leading to greater volatility and higher total risk relative to the 1-month portfolio.

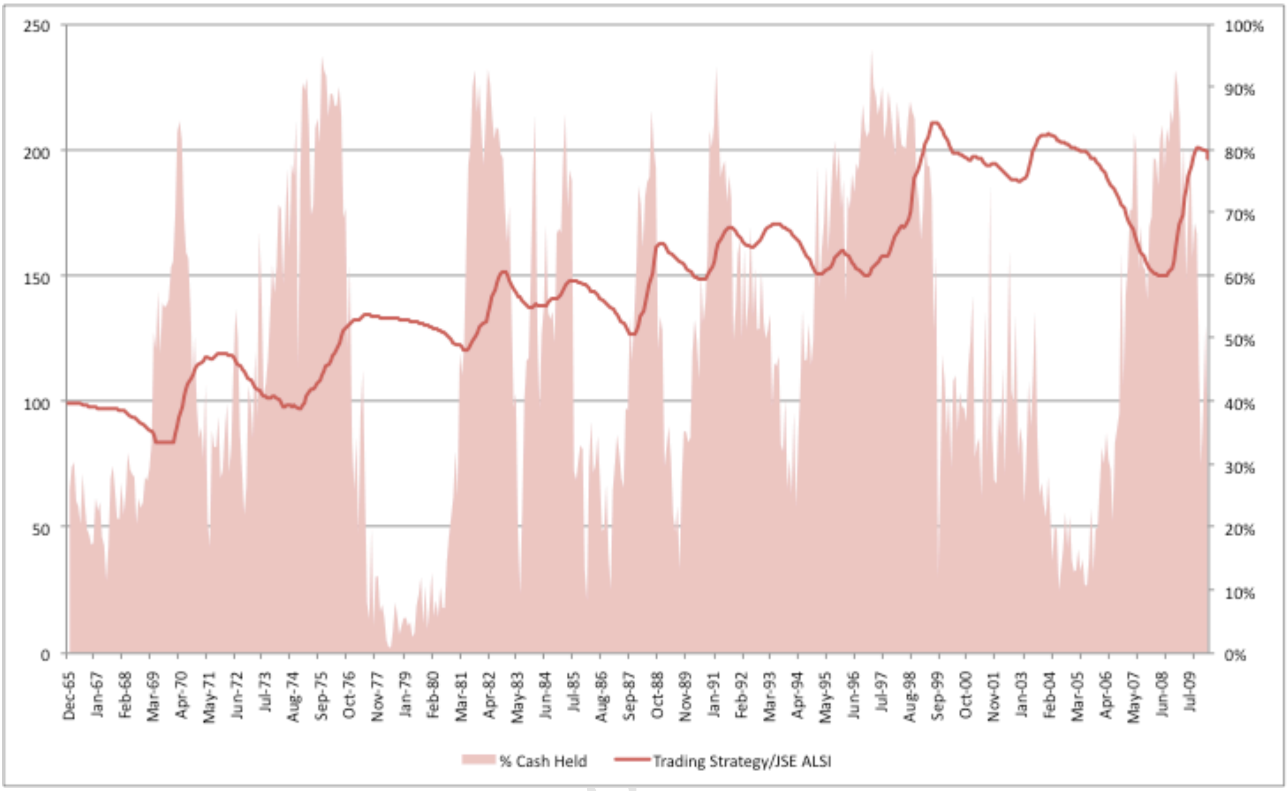
The above graphs are useful for analysing trends of the two indices, but to compare relative outperformance/underperformance of the two portfolios against the JSE ALSI, the relative values of the two portfolios against the JSE ALSI are graphed below.

Figure 6.12 Cumulative Outperformance of 1-Month Trading Strategy B relative to the JSE ALSI



Reflecting the results from the graph above, there is a clear negative trend through time, indicating underperformance relative to the JSE ALSI. The rationale is the same as explored above: with the expected probabilities of outperformance clustered around 50%, the portfolio construction results in the weightings of the portfolio to hover around an equally-weighted portfolio between the JSE ALSI and the risk-free cash asset. As a result, the portfolio outperforms the JSE ALSI when the ALSI is yielding negative returns, as the ALSI negative returns are buffered by the positive, albeit small, returns yielded from the risk-free asset, and vice versa. The JSE ALSI however tends to have more periods of positive returns than negative returns, and, as such, the portfolio tends to underperform relative to the JSE ALSI.

Figure 6.13 Cumulative Outperformance of 12-Month Trading Strategy B relative to the JSE ALSI



The expected return pattern signature from this portfolio construction is more visibly evident for a 12-month holding period than for a 1-month holding period, mainly because the greater variation in forecast probabilities leads to a greater proportion of the investment to be invested in one of the two asset classes. When there is a large weighting in the JSE ALSI, due to a high probability of expected positive returns, the portfolio generally underperforms relative to the ALSI, as the portion retained in the risk-free alternative reduces the total return of the portfolio. However, when there is a large weighting in the risk-free asset, due to expected negative returns in the ALSI, the movement of weights away from the negatively performing JSE ALSI leads to relative outperformance.

As a 12-month holding period leads to probabilities of expected positive returns that are closer to zero and one hundred percent compared to a 1-month holding period, when the predicted return are of the correct sign (and therefore the p-value is on the correct side of 0.5), the underperformance realised during periods of expected JSE ALSI positive performance is less marked and the outperformance realised during periods of expected JSE

ALSI negative performance is more marked. However, this strategy also provides greater protection, as can be seen in 1994, when, even though the weighting in a risk-free asset is not substantially different from 50%, the buffer from the stable asset generates outperformance in a strongly declining market.

Although 1994 provides the most noticeable case, the portion of a risk-free asset that is held throughout the sample does provide protection against incorrect forecasts. As a result, the portfolios constructed from this trading strategy have significantly lower standard deviations than the respective portfolios constructed from Trading Strategy A, leading to higher total risk-adjusted returns.

Trading Strategy C

For a holding period of 1 to 6 months, in absolute terms the third trading strategy is the worst performing strategy, and underperforms the JSE ALSI. For 12 and 24-month return holding periods, Trading Strategy C outperforms relative to the JSE ALSI and Trading Strategy B, but underperforms relative to Trading Strategy A, with the highest absolute return being realised over a 24-month holding period (19.65%).

However, Trading Strategy C consistently provides the highest return per unit of risk, with 1-month returns providing the highest risk-adjusted return of 3.81. When taking only market risk into account, Trading Strategy C consistently has the highest Jensen's alpha, with 12-month returns providing 7.26% returns in excess of the expected return of a portfolio with the same level of systematic risk. These higher alphas are most likely caused by the low betas between the portfolios and the JSE ALSI, as the portfolio construction leads to high proportions of a risk-free asset being held compared to the JSE ALSI. Trading Strategy C also tends to have the same or fewer calendar years of outperformance compared to the other two trading strategies, with 3-month returns providing the most consistent performance (22 calendar years of outperformance).

As in the other two strategies, the percentage of cash held as a proportion of the entire portfolio decreases as the holding period increases. The same reasoning can be applied to this result: longer return periods have a larger variation around zero, causing the probabilities of positive or negative performance to be spread over a larger range. There is also a positive trend in the JSE ALSI, which will be more noticeable in longer return periods. As

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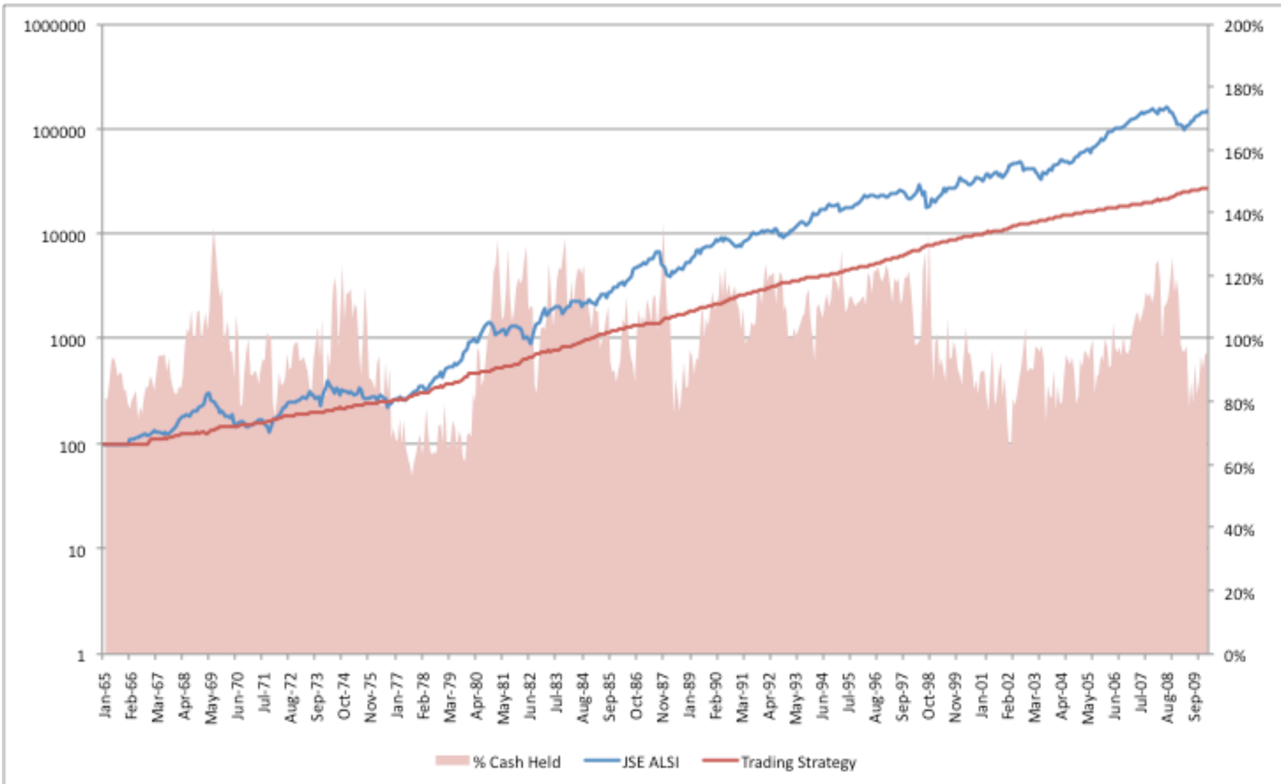
a result, there are strong positive signals, leading to stronger weighting movements to the JSE ALSI for longer holding periods than for shorter holding periods.

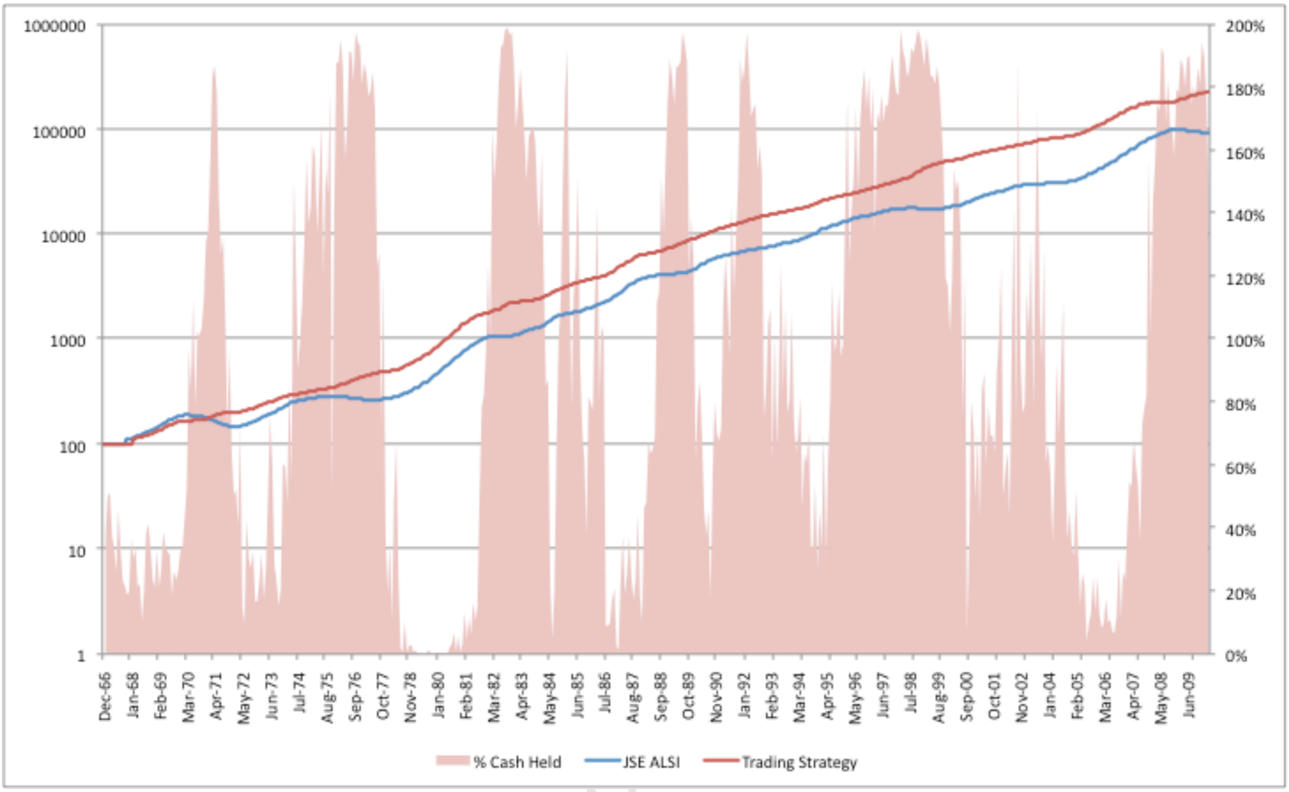
To examine the portfolio return patterns, the cumulative returns of the holding period with the highest absolute returns (24-month) and highest risk-adjusted returns (1-month) are plotted against the JSE ALSI over the same time period (using a log-scale to allow for visual analysis).

Figure 6.14 Cumulative Value of 1-Month Trading Strategy C relative to the JSE ALSI



The graph above illustrates the results highlighted above. A portfolio constructed with a 1-month holding period has a very stable proportion of cash held in a risk-free asset throughout the sample period, leading to returns that are very stable, but are lower than the returns that can be exploited from the ALSI. However, from 1966-1972 and again from 1972-1977, the market receives returns in excess of the portfolio for a period for several years and then subsequently loses this value over the next several years. From 1977, however, the gains received on the JSE ALSI are larger relative to the losses sustained, leading to the pattern of outperformance of the JSE ALSI from that period onwards.

Figure 6.15 Cumulative Value of 24-Month Trading Strategy C relative to the JSE ALSI

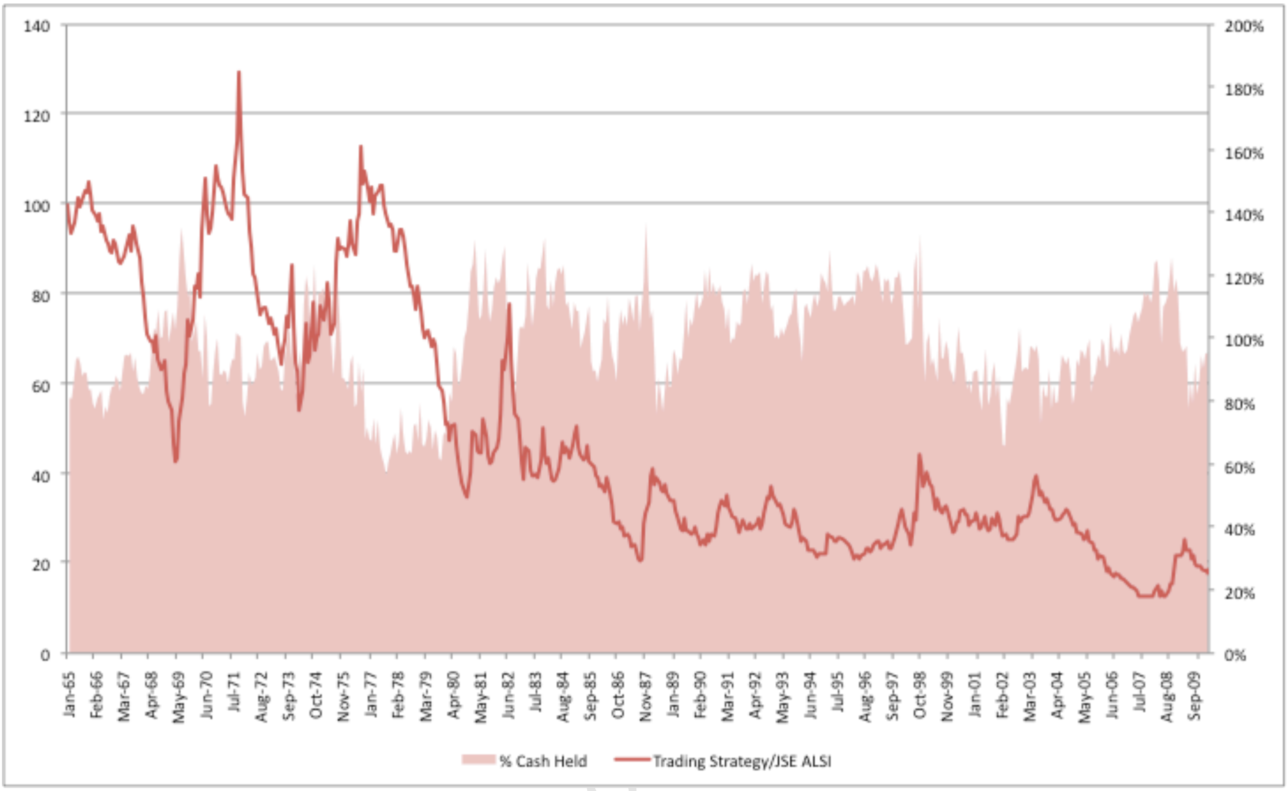


Before 1970, Trading Strategy C grew at a slightly lower rate than the JSE ALSI. However, as the market starts to turn towards a downward swing, cash holdings and the short position of the portfolio increase and performance remained steady as the JE ALSI loses some of the gains it has previously realised. From that period onwards, Trading Strategy C retains a higher cumulative value than the JSE ALSI, although it is clear that the magnitude of that difference varies through the market cycle, decreasing during periods of positive market performance and increasing during periods of negative market performance.

In general, the 24-month holding period portfolio has returns that follow the same general shape of the JSE ALSI, but which can still generate positive returns when the market has negative returns, leading to a more stable pattern of returns that exceed the returns realised on the JSE ALSI.

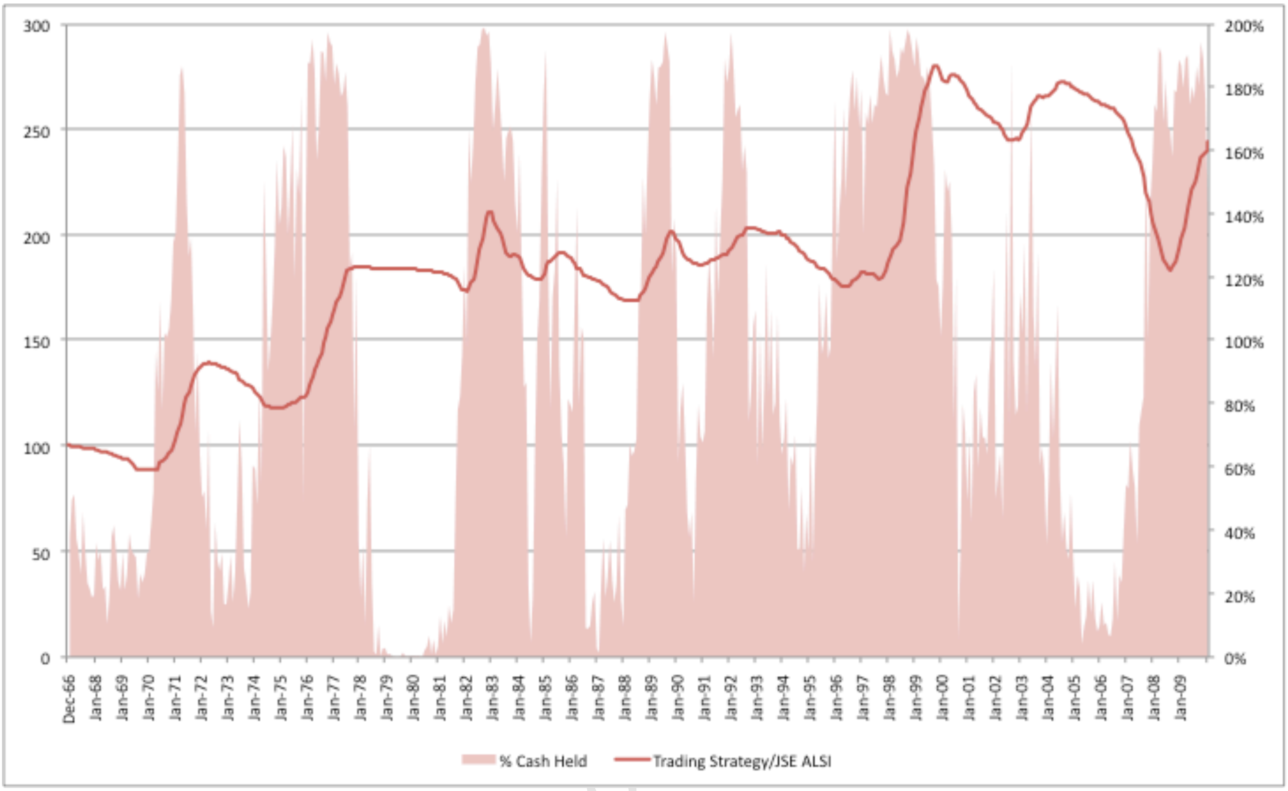
To understand the periods of outperformance and underperformance, the cumulative outperformance of Trading Strategy C applied to a one-month holding period relative to the JSE ALSI is plotted below.

Figure 6.16 Cumulative Outperformance of 1-Month Trading Strategy C relative to JSE ALSI



Before 1977, the pattern of outperformance suggests that the forecast model is correctly predicting the movement in the market, leading to the strategy generating 1.5 times the returns of the JSE ALSI by 1977. However, after 1977, cash holdings are higher than 100% leading up to a market downswing (leading to greater underperformance) and during a market downswing (leading to outperformance that in general exceeds the previous excess underperformance). However, it is clear that there is a consistent trend of underperformance post-1977 as the portfolio is never able to fully realise the positive long-term market trend.

Figure 6.17 Cumulative Outperformance of 24-Month Trading Strategy C relative to JSE ALSI



In general, the pattern of outperformance illustrates market timing ability. During periods when the market is performing, cash positions are relatively small, and the portfolio is able to realise most of the returns generated by the JSE ALSI, and, as such, performance nearly matches that of the JSE, illustrated by a flat slope in the graph above. During periods when the market is earning negative returns, the portfolio switches to a strong cash and short position, leading to returns being generated by both the position in the risk-free asset and by the short position in the declining JSE ALSI. However, there are times when the switch to this position comes to early, leading to strong underperformance. The most noticeable period is from 2005-2008, when the market is performing very strongly. The forecast model suggests that a crash is imminent, but the signal comes too early, and the portfolio becomes strongly invested in a short position. This leads to very poor performance during the time period, and although this is followed by a period of outperformance as the sub-prime crisis occurred, the underperformance in the build-up to the crash is not fully reversed. Although the build-up to the sub-prime crisis is the most noticeable example, this pattern of the correct position being taken too early also occurred between 1974-1975 and 1983-1985.

Conclusions

The most noticeable conclusion is that it is possible to exploit a predictive timing model and generate returns in excess of those realised by the JSE ALSI. In addition, these findings illustrate that different choices in implementing these forecasts in a trading strategy generates very different return performance and pattern. Trading Strategy A, the most simplistic as it takes a 100% position in one of two asset classes, generates the highest absolute returns, but with the greatest levels of total risk. Trading Strategy C, the most complicated as it includes both the strength of the prediction and allows for short positions, leads to the lowest levels of total risk and the highest levels of risk-adjusted returns. The third conclusion is how the choice in portfolio holding periods leads to different results. A 1-month holding period consistently leads to the highest risk-adjusted returns, possibly due to the lower variation in forecasts around 50%, but also to the lowest absolute returns. Longer return horizons, such as 12-month returns for Trading Strategies A and B and 24-month returns for Trading Strategies C, lead to the highest absolute returns, but with higher risk, as the forecasts average above 50% (due to the positive long-term trend of the market) and have a greater variation.

In summary, there is evidence that suggests that it is possible to time the market. However, both the choice of exploiting the forecast model that attempts to forecast market performance and the choice in return horizon lead to great variation in the nature of returns.

However, the forecast models used to develop this trading strategy only uses information pertaining to the return horizon being considered, thereby not using the information content inherent in the forecast models of longer return horizons. For example, if an investor is looking at 12-month returns and only uses the 12-month predictive forecast above, they will be losing out on the information content in the 24-month forecast. The next chapter explains the method to include this information content and augments the model developed above with this information.

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7 Results: Implicit Forecast Augmented Multifactor Forecast Models

The previous chapter finds evidence that forecasts generated using OLS estimation of significant forecasting variables is both able to partially predict movements in the JSE ALSI, as well as be implemented in trading strategies that outperform the JSE ALSI. This suggests that the forecasts have a certain information content embedded in them, which could be further extracted with the aim to better forecast the JSE ALSI. In section 7.1, the methodology to utilise long-term forecasts in shorter-term forecast models is presented and the success of the augmented model in predicting the JSE ALSI is analysed. In section 7.2, the forecasts generated in 7.1 are applied to three trading strategies, and the performance and characteristics of performance relative to the JSE ALSI is analysed.

7.1 Methodology and Estimation of Implicit Forecast Augmented Multifactor Forecast Models

The implicit forecast augmented multifactor forecast model has two changes from the multifactor predictor model in the previous chapter. The first is a change of dependent variable from JSE ALSI returns to excess JSE ALSI returns above the risk-free asset returns, using the 90-day Banker's Discount Rate as a proxy. This change therefore directly forecasts whether the JSE ALSI is going to out or under-perform relative to a proxy of the risk-free rate. The second change is to include the information content that exists in the forecasts created by models that predict returns for longer than the relevant return holding period. To include the information content requires the creation of a new variable, called the implicit forecast variable. Mathematically, the implicit forecast is defined as $\overline{Y}_{t,t+T} = E\left[Y_{t-Z,t+T} \mid X_{t-Z}\right] - R_{t-Z,t}$; $Z > T > 0$, where $\overline{Y}_{t,t+T}$ is the forecasted return on the market from period t to period t+T, $R_{t,t-Z}$ is the actual return realised from period t-Z to period t, T is the length of the short-term forecast, T+Z is the length of the long-term forecast, X_i is a vector of variables, at time t-Z, used to generate the long-term forecast and Z > T; Z > 0; T > 0. These implicit forecasts are then added to the initial forecast models to create an augmented forecast model.

The final multifactor forecast model includes all variables in the initial forecast models, with the addition of all the implicit forecasts that would be available for a hypothetical investor. To test whether there is overall significance, the adjusted f-statistic (f-statistic divided by number of months in a return horizon) is used to adjust

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for return dependency. The addition of the implicit forecast variables is also tested for overall significance using the restricted least-squares methodology with an adjusted f-statistic (adjusted as above). The results of these estimations are presented below.

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Table 7.1 Summary of Augmented Multifactor Forecast models OLS Estimations

	1 Month Returns		3 Month Returns		6 Month Returns		12 Month Returns	
Intercept	-0.0085	(0.67)	0.0287	(0.42)	-0.0269	(0.70)	0.0559	(0.66)
Cointegration Residual	0.0006	(0.99)	**-0.1233**	(0.04)	-0.0824	(0.47)	**-0.4524**	(0.04)
Earnings Yield	-0.1340	(0.30)	-0.4791	(0.20)	-0.1549	(0.81)	-0.7283	(0.54)
RBAS Adjusted EY	0.0077	(0.30)	0.0276	(0.18)				
24-Month Earnings Growth							-0.2793	(0.18)
90-Day Overbought/Sold	0.9939	(0.32)						
5 Year Overbought/Sold					**0.2327**	(0.04)	0.1605	(0.47)
1-Month Returns	-0.2486	(0.44)						
36-Month Returns							-0.0237	(0.90)
48-Month Returns	0.0078	(0.60)	-0.0091	(0.78)	-0.1197	(0.16)		
3-Month Implicit Forecast	0.3601	(0.34)						
6-Month Implicit Forecast	-0.0194	(0.56)	**-0.1801**	(0.07)				
12-Month Implicit Forecast	-0.0076	(0.79)	0.0136	(0.88)	0.1089	(0.53)		
24-Month Implicit Forecast	0.0343	(0.12)	**0.1172**	(0.09)	**0.3738**	(0.00)	0.3923	(0.12)
Adjusted R^2	0.03		0.11		0.25		0.38	
Overall Model Adjusted F-Statistic	**2.5540**	(0.01)	**5.9217**	(0.00)	**12.1616**	(0.00)	**15.4722**	(0.00)
Implicit Forecast RLS Adjusted F-Statistic	**2.0618**	(0.08)	**5.7572**	(0.00)	**18.3209**	(0.00)	**13.4056**	(0.00)

OLS Coefficients (adjusted p-values in brackets). All bolded figures are significant at the 10% level. ALSI Sample Period: 1 January 1960 – 31 January 2010. Earnings Yield is measured as EPS/P. RBAS Adjusted Earnings Yield is measured as EY/RBAS. % Overbought/Sold is measures as $(P_{ALSI}-MA_{ALSI})/MA_{ALSI}$. T-period historic returns are calculated as $\ln(ALSI_t)-\ln(ALSI_{t-T})$. Cointegration residual is calculated as the difference between the actual log of the ALSI and the predicted log of the ALSI according to the OLS cointegrating regression tabulated in table 4.3.2. Implicit forecast is calculated as the difference between the predicted T-period return and the actual return achieved at period t +T-R, where R is the return timeframe. Adjusted F-statistic is F-statistic divided by forecast horizon, such that $\overline{F} = \frac{F}{M}$.

This table must be interpreted with caution. Due to the high level of potential multicollinearity and the various predictors that are chosen, the coefficients can vary wildly from return timeframe to return timeframe. However,

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it is evident that the significance of individual variables is generally weak. Despite the weak individual significance of the variables, the f-statistics of overall significance are significant at the 10% level, even after adjustment for return dependency.

To determine whether the inclusion of the implicit forecasts improves the model, the table below compares the adjusted R^2 of the original model with the adjusted R^2s of the augmented model.

Table 7.2 Adjusted R^2 of Forecast models

	1-Month Returns	3-Month Returns	6-Month Returns	12-Month Returns
Excluding Implicit Forecasts	0.03	0.07	0.12	0.32
Including Implicit Forecasts	0.03	0.11	0.25	0.38

The table above illustrates a very similar predictive power, once adjusting for extra explanatory variables, for 1-month returns, a slight improvement in predictive power for 3 and 12-month returns, and a substantial increase in predictive power for 6-month returns. The results of the restricted f-test (included in Table 6.2.1) are used to determine whether these improvements are statistically significant. The joint significance of the implicit forecasts is significant at the 10% level across return timeframes, confirming their relevance.

Individually, the 24-month implicit forecast variable is significant and positive at the 10% level for 3 and 6-month return timeframes, and is positive and the most significant and second most significant variable for 1 and 12-month return timeframes respectively (albeit not being statistically significant at the 10% level). The 6-month implicit forecast is also significant, at the 10% level, for a 3-month return timeframe; however, it is negative. As the implicit forecasts should be positive (if the longer forecast is correct, the difference in returns realised at t and the forecast returns should correct in the next time period), this is not an expected result. A possible explanation is due to a momentum effect being implicitly included in the forecast coefficient – a market that outperforms its expected 6-month return over 3-months continues to outperform as the momentum behind it increases and vice versa. The significance of the 24-month implicit forecast for the same return timeframe also suggests that the two variables are moderating the information content that each individual variable holds. 6 and

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12-month implicit forecasts are also negative for 1-month returns; however these are not statistically significantly different from zero. All other implicit forecasts are positive as expected.

The significance of the cointegrating residual, which is the strongest variable in the prior models, is still significant at the 10% level for 3 and 12-month return timeframes; however it is not statistically significant for 1 and 6-month returns. The implicit forecast variable for these return timeframes could be including the same information content of a long-term mispricing of the JSE ALSI as the cointegrating residual, causing collinearity between the two variables and reducing their individual significance. This does not occur in 3 and 12-month return timeframes as the two variables have different information contents, leading to a stronger relationship existing when both are included. Apart from 1-month returns, where the variable is not statistically significant, the coefficient on the cointegrating residual is negative, indicating movements away from the long-term cointegrating relationship correct in the following time periods. However, except for 12-month returns, the absolute value of the coefficient is substantially below one, implying that corrections take several time periods to filter through. The coefficient on 12-month returns is -0.45, implying that it takes slightly over two time periods for any correction to the fundamental mean value to occur.

The only other significant coefficient that is significant at the 10% level is for the relationship between the 5-year overbought/sold indicator and 6-month returns. The coefficient is positive (as it is for the relationship between the 5-year overbought/sold indicator and 12-month returns), which suggests that any long-term momentum effect persists in these time periods. As one would expect momentum to correct, this is a peculiar result, but one must also account for the inclusion of the other momentum variable, historic returns. As the coefficients on historic returns are negative for these time periods, albeit not significant at the 10% level, it suggests that the momentum due to price changes corrects in these time periods, but momentum from relative value from a long-term mean will persist over the time period. These results are also consistent from the results of the original forecast model, indicating that this is a robust finding.

The coefficient of 90-day overbought/sold indicator with 1-month returns is positive, although not significant at the 10% level. This is consistent with the results from the initial model, thereby suggesting a more robust finding.

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However, the coefficient between 1-month historic and future returns is negative, albeit not significant at the 10% level, which is the opposite of the finding from the original model. 48-month historic returns have a positive relationship with 1-month returns which is not significant at the 10% level. The lack of significance is consistent with the original model findings, but the coefficients are different. However, due to the lack of individual significance, this contradiction is not particularly surprising. 48-month returns remains negative and not significant at the 10% level for 3 and 6-month returns, which is consistent with the original model.

24-month earnings growth, which is significant in the initial estimation results, is not significant at the 10% level in the augmented model, although it remains negative. As the 24-month implicit forecast is the only variable included, it stands to reason that earnings growth and this implicit forecast both have some element of information mutual between the variables (and as the 24-month implicit forecast uses earnings growth to achieve its forecast, this is a more reasonable assumption) leading to weaker individual significance.

Overall, the above findings suggest that the additional information content within the implicit forecasts add forecasting power to the forecast models. For certain variables, the implicit forecast is a better indicator of information and its inclusion leads to a decrease in significance of the variable. However, the model as a whole is an improved. Another test for model performance, as well as for any evidence of forecast bias, is to regress predicted returns against actual returns. If the model is a perfect predictor of returns, the R^2 will be 100% and if there is no forecast bias, the intercept coefficient will be zero and the slope coefficient would be one. The results of these regressions on the relevant time periods and dependent variable of both the initial and the augmented models, as well as a scatter plot of actual versus predicted returns of the augmented model, are provided below.

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Table 7.3 OLS Estimations of Predicted versus Actual Returns

	Augmented Model					Initial Model				
	Intercept		Slope		R^2	Intercept		Slope		R^2
1-Month Retuns	**0.0015**	(0.01)	**0.0481**	(0.00)	0.05	**0.0097**	(0.00)	**0.0326**	(0.00)	0.03
3-Month Returns	**0.0041**	(0.02)	**0.1236**	(0.01)	0.12	**0.0278**	(0.00)	**0.0723**	(0.00)	0.07
6-Month Returns	**0.0060**	(0.08)	**0.2596**	(0.02)	0.26	**0.0523**	(0.00)	**0.1295**	(0.00)	0.13
12-Month Returns	0.0071	(0.20)	**0.3867**	(0.02)	0.39	**0.0801**	(0.00)	**0.3310**	(0.00)	0.33

OLS Coefficients (p-value of individual significant difference from 0 for intercept, 1 for slope) and R^2

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Figure 7.1 1-Month Predicted versus Actual Returns

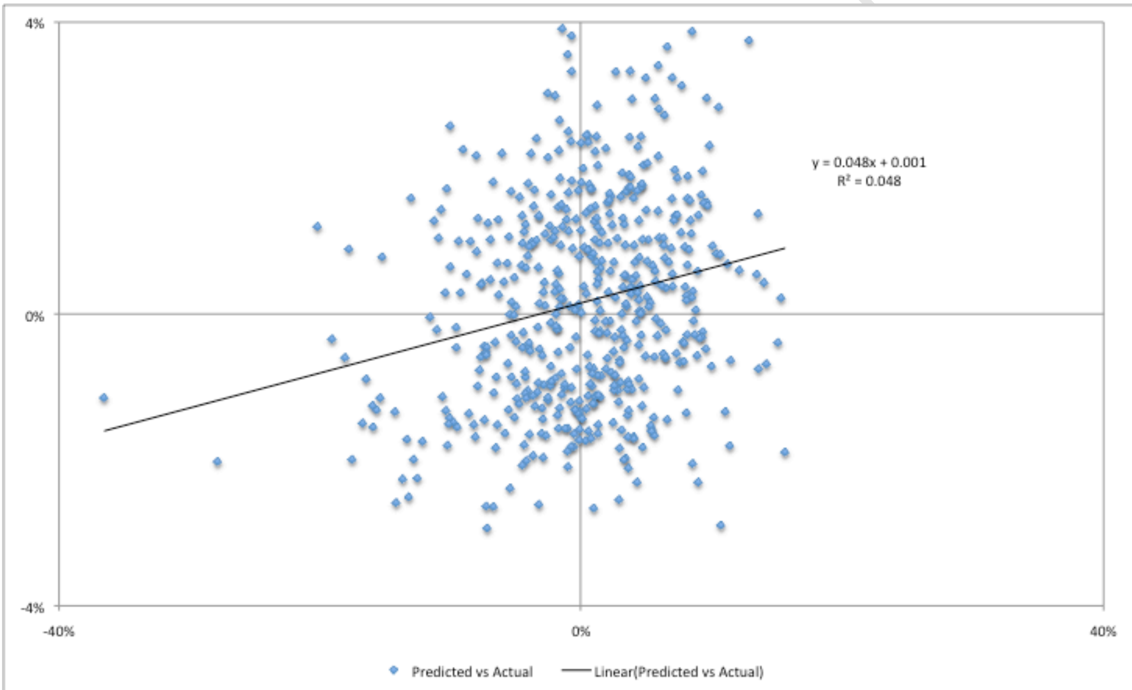


Figure 7.2 3-Month Predicted versus Actual Returns

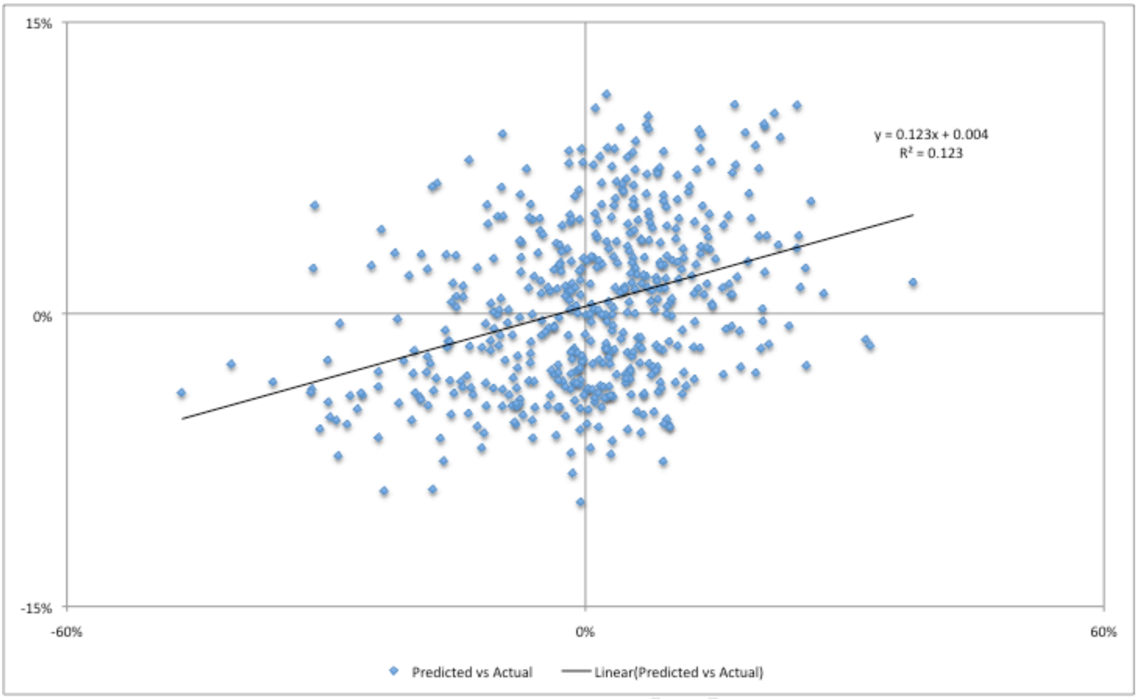


Figure 7.3 6-Month Predicted versus Actual Returns

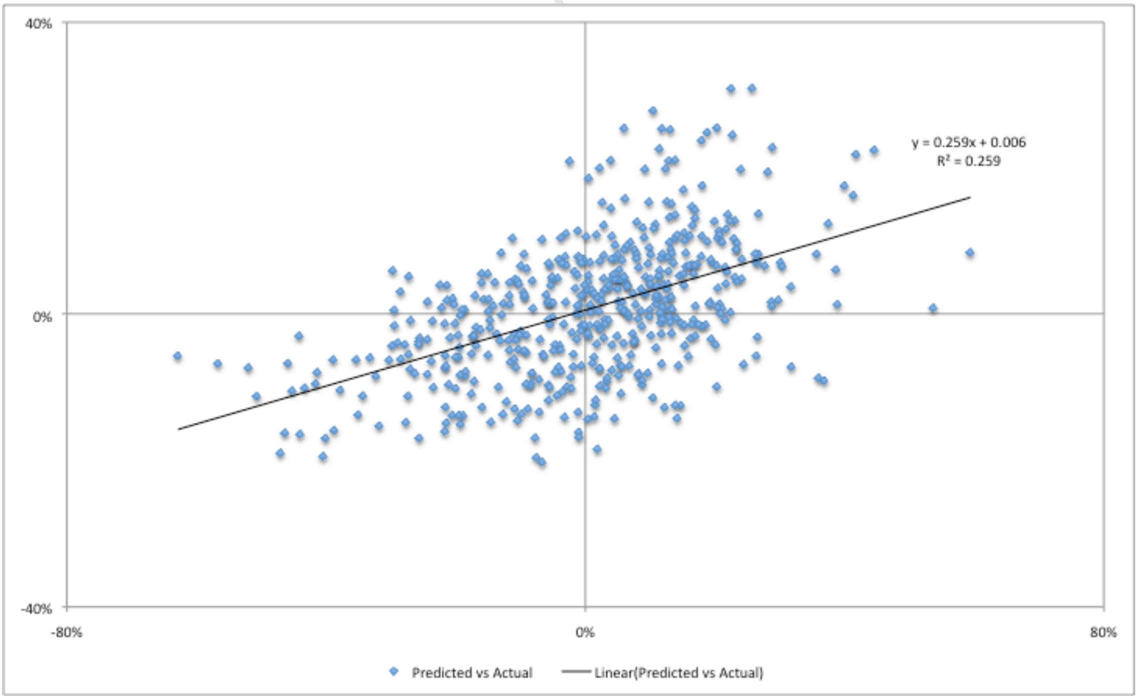
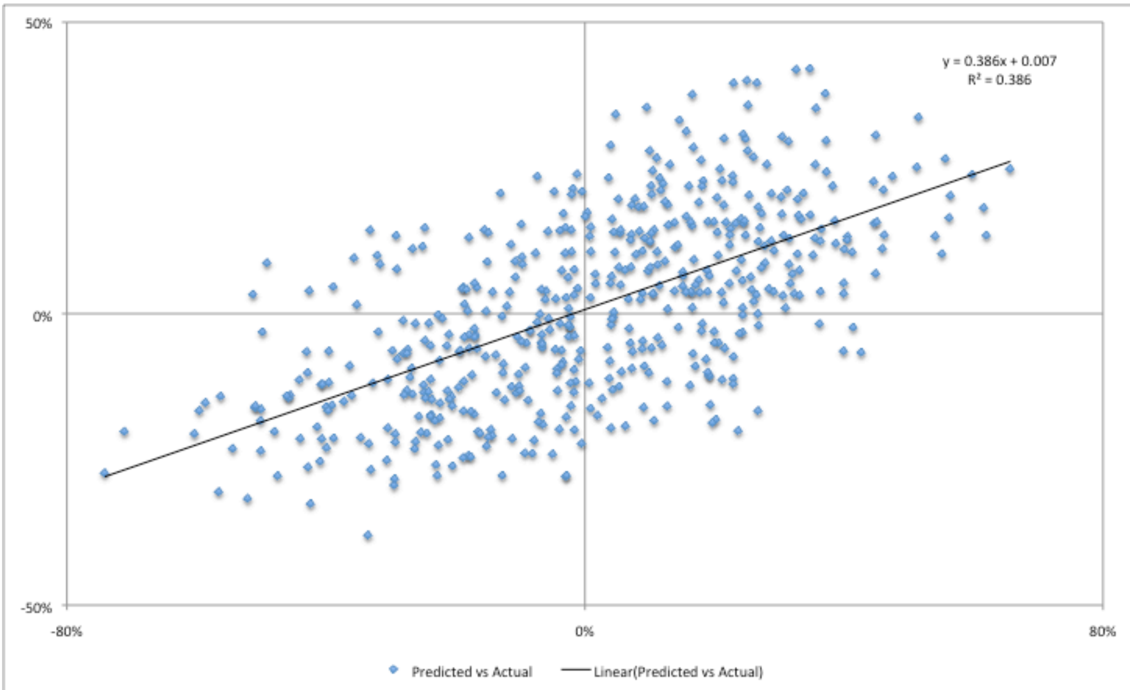


Figure 7.4 12-Month Predicted versus Actual Returns



It is clear from the results that the forecasts stemming from the augmented model are different from the perfect case. Across return timeframes the intercept is constantly positive, the slope coefficient is constantly less than one and the R^2 is less than 100%. Like the initial model, longer return horizons are closer approximates of the perfect case, but even the forecasts of the longest return horizon, 12-month returns, can only explain 39% of variation in returns. From the regression results and a visual analysis of the scatter plots, several conclusions can be drawn.

Firstly, the positive intercept indicates that there is a positive forecast bias, although it is not statistically significant at the 5% level for a 6 and 12-month return horizon. The augmented model will predict a positive return of 0.15% for 1-month returns to slightly over 0.7% for 12-month returns when actual returns will be zero. This is problematic because the augmented model will incorrectly estimate the directions of returns when the absolute magnitude of returns is close to zero.

Secondly, the forecasts from the augmented model have a smaller spread compared to actual returns, as can be seen by a slope coefficient significantly less than one. Thus the model will significantly understate, in absolute terms, large movements in the JSE ALSI. However, this finding is less problematic than the initial finding, as the direction of returns will still remain correct.

Thirdly, the predictive power of the augmented model is significantly less than the ideal case, with the best predictor, over 12-months, only explaining 39% of variation in returns. For 1-month returns, the forecast model only explains 5% of variation. These figures indicate that the models lack the ability to consistently and accurately predict future returns.

Finally, although the augmented model does not closely approximate that of a perfect forecast model, it is an improvement over the initial model. The positive forecast bias is substantially smaller in the augmented model, with the largest bias in the augmented model still smaller than the smallest bias in the initial model. The augmented model's forecasts also more closely fit the spread in actual returns. Finally, the predictive power of the augmented model yields an increase in predictive power ranging of roughly 2 to 13%, dependent on the return timeframe. Therefore, the forecasts from the augmented model are better forecasters of actual returns than the initial model.

However, it is incredibly difficulty to predict both the magnitude and directions of share returns. A better measure of predictive power would be to determine the ability of the model to predict the direction of share returns (i.e. the percentage of positive forecasts followed by positive returns and negative forecasts followed by negative returns). The hit-rate is once again used as a measure of the augmented model's performance, compared with a benchmark hit-rate of a model that consistently predicted positive returns. As the augmented model forecasts returns in excess of the compounded risk-free rate over the return horizon while the initial model forecasts only the return of the JSE ALSI, they cannot be compared directly. Instead, the increase in hit-rates relative to the models' respective benchmarks is used to compare the two models performance in predicting return direction. The results are tabulated below.

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Table 7.4 Hit-Rate of Forecasts

Return Horizon	Augmented Model	Benchmark
1-Month Returns	57.64%	56.29%
3-Month Returns	61.70%	60.54%
6-Month Returns	68.86%	62.28%
12-Month Returns	76.21%	59.57%

Table 7.5 Augmented and Initial Models' Hit-Rates Difference relative to Benchmark

Return Horizon	Augmented Model	Initial Model
1-Month Returns	1.35%	-1.48%
3-Month Returns	1.16%	-4.28%
6-Month Returns	6.58%	-1.87%
12-Month Returns	16.64%	1.70%

Difference calculated as(Hit-Rate Model) – (Hit Rate Benchmark)

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As the hit-rates are greater than the benchmark across all return horizons, it suggests that the augmented model provide a superior ability to forecast the direction of excess returns than assuming consistent JSE ALSI returns in excess of the 90-day Bankers' Discount Rate. The greatest difference is for 12-month returns, with the augmented forecast model predicting the direction of returns by an additional 16.64% relative to its benchmark. This finding is peculiar because the benchmark hit-rate is the second lowest for a 12-month period, which is contrary to both the trend in the hit-rates and the concept that the JSE ALSI is an increasing series. However, this occurs as a result of slightly different starting sample periods, with 12-month returns being calculated from a relative peak, thereby leading to more initial negative excess returns.

The augmented model consistently forecasts market directions more accurately than the benchmark, irrespective of return horizon. As the initial model, with the exception of 12-month returns, forecasts market directions less accurately than the benchmark, it indicates that the inclusion of the implicit forecasts adds directional forecasting ability to the forecast model. Even in the 12-month return horizon, the augmented model is a substantially superior predictor of excess return direction relative to its benchmark compared to the initial model's hit-rate relative to its benchmark. The results once again support the finding that there is an improvement in predictive power of the augmented model relative to the initial model.

However, the hit-rate does not factor in the impact of an incorrect return direction call. Thus, if the model incorrectly forecasts the directions of returns that are small in absolute magnitude but correctly forecasts the direction of returns that are large in magnitude, it will provide superior returns than a pure buy-and-hold strategy.

7.2 Performance of Implicit Forecast Augmented Multifactor Forecast Model Applied to Trading Strategies

To take this into account, the same three trading strategies used to test the performance of the initial model are constructed, and their performance metrics compared with the JSE ALSI. These strategies require a prediction in the form of a probability of the JSE outperforming a risk-free alternative. As the dependent variable of the augmented model is the excess return of the JSE ALSI, the forecasts are transformed into a probability of outperformance using a normal distribution with a standard error equal to the standard error of the regression.

To test performance, the annualised average geometric returns, standard deviations, risk-adjusted returns (measured as annualised average geometric return/annualised standard deviation), Jensen's alpha and the portfolio return beta with the ALSI will be used as performance metrics and compared to the JSE ALSI. Years of over, under and identical performance will also be presented, as well as the average percentage held in cash. Finally, the trading strategies will be compared with each other to determine the one with superior performance. For convenience, a summary of the strategy rules is provided below.

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Table 7.6 Trading Strategy Rules

	Trading Strategy A	Trading Strategy B	Trading Strategy C
JSE ALSI	100% if p > 50%; 0% if p <= 50%	p%	(2p – 100)%
RBAS	0% if p > 50%; 100% if p <= 50%	(100-p)%	(200 – 2p)%

P is the forecasted probability that the JSE ALSI will yield a positive return over the relevant holding period.

To implement strategies longer than one-month, it is assumed that the investor breaks up their investment into x equal portions, where x is the length of the return horizon, and invests each portion for the full length of the forecasts return horizon at time t.

The performance metrics of these trading strategies relative to a pure buy-and-hold strategy in the JSE ALSI are reported below.

Table 7.7 Summary of Trading Strategy Results relative to JSE ALSI

		Trading Strategy A	Trading Strategy B	Trading Strategy C	JSE ALSI
1-Month	Average Annualised Return	23.03%	16.79%	14.23%	17.80%
	Annualised Standard Deviation	14.92%	11.21%	4.03%	22.41%
	Risk-Adjusted Return	1.54	1.50	3.53	0.79
	Average % Cash	47.58%	49.06%	98.11%	0%
	Annualised Jensen's Alpha	8.07%	1.64%	3.31%	0%
	Calendar Years Outperformance	21	20	19	
	Calendar Years Underperformance	12	23	24	
	Calendar Years Same Performance	10	0	0	

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Table 7.7 Summary of Trading Strategy Results relative to JSE ALSI

3-Month	Average Annualised Return	23.05%	17.93%	16.33%	17.79%
	Annualised Standard Deviation	17.03%	12.81%	7.03%	24.31%
	Risk-Adjusted Return	1.35	1.40	2.32	0.73
	Average % Cash	48.55%	48.59%	97.17%	0%
	Annualised Jensen's Alpha	7.85%	2.53%	5.12%	0%
	Calendar Years Outperformance	21	24	22	
	Calendar Years Underperformance	14	19	21	
	Calendar Years Same Performance	8	0	0	
6-Month	Average Annualised Return	23.47%	19.20%	18.79%	17.65%
	Annualised Standard Deviation	18.84%	14.53%	11.24%	25.70%
	Risk-Adjusted Return	1.25	1.32	1.67	0.69
	Average % Cash	45.65%	48.49%	96.98%	0%
	Annualised Jensen's Alpha	7.92%	3.71%	7.49%	0%
	Calendar Years Outperformance	20	19	19	
	Calendar Years Underperformance	15	24	24	
	Calendar Years Same Performance	8	0	0	
12-Month	Average Annualised Return	21.84%	19.22%	19.50%	17.32%
	Annualised Standard Deviation	21.20%	17.15%	14.34%	27.01%
	Risk-Adjusted Return	1.03	1.12	1.36	0.64
	Average % Cash	47.97%	48.43%	96.86%	0%
	Annualised Jensen's Alpha	6.30%	3.76%	7.52%	0%
	Calendar Years Outperformance	21	20	20	
	Calendar Years Underperformance	12	23	23	
	Calendar Years Same Performance	10	0	0	

Sample Period: January 1965 – January 2010. Average Annualised Returns are calculated as average t-period returns over the sample period multiplied by 12/t. The Annualised Standard Deviations are calculated as the standard deviation of returns over the sample period multiplied by the square root of 12/t. Risk-Adjusted Returns are calculated as average annualised return/annualised standard deviation. Annualised Jensen's alpha is calculated as the annualised C in the regression equation: Excess Returns(Trading Strategy) = C + Beta(Excess Returns(JSE ALSI))

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Trading Strategy A

Like the trading strategies based on the initial forecast model, the optimal return horizon for the trading strategy based on the augmented forecast model is dependent on the choice of performance metric. The 6-month trading strategy yields the highest average annualised return (21.84%). However, it has the most calendar years of underperformance (15) and the fewest calendar years of outperformance (20). The trading strategy applied to a 1-month return horizon yields the lowest standard deviation (14.92%), the highest risk-adjusted return (1.54), the highest Jensen's alpha (8.07%) and the most calendar years of outperformance (21, the same number of years as 3, 6 and 12-month horizons). Unlike the strategy based on the initial forecast model, there is not a clear trend in the average percentage of cash held, with 3-month returns holding cash the most often (48.55%) and 6-month the least (45.65%).

However, irrespective of return horizon, trading strategy A generates superior performance across all metrics compared to a pure buy-and-hold strategy in the JSE ALSI. To determine its performance relative to the trading strategy derived from the initial forecast model, the table below summarises the performance metrics of both trading strategies.

Table 7.8 Comparison of Trading Strategy A from Augmented Model relative to Initial Model

		Augmented Model	Initial Model
1-Month	Average Annualised Return	23.03%	20.78%
	Annualised Standard Deviation	14.92%	14.96%
	Risk-Adjusted Return	1.54	1.39
	Average % Cash	47.58%	47.04%
	Annualised Jensen's Alpha	8.07%	6.22%
	Calendar Years Outperformance	21	19
	Calendar Years Underperformance	12	14
	Calendar Years Same Performance	10	11

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Table 7.8 Comparison of Trading Strategy A from Augmented Model relative to Initial Model

3-Month	Average Annualised Return	23.05%	21.26%
	Annualised Standard Deviation	17.03%	17.26%
	Risk-Adjusted Return	1.35	1.23
	Average % Cash	48.55%	47.77%
	Annualised Jensen's Alpha	7.85%	6.30%
	Calendar Years Outperformance	21	20
	Calendar Years Underperformance	14	13
	Calendar Years Same Performance	8	11
6-Month	Average Annualised Return	23.47%	21.58%
	Annualised Standard Deviation	18.84%	18.57%
	Risk-Adjusted Return	1.25	1.16
	Average % Cash	45.65%	47.10%
	Annualised Jensen's Alpha	7.92%	6.47%
	Calendar Years Outperformance	20	16
	Calendar Years Underperformance	15	17
	Calendar Years Same Performance	8	11
12-Month	Average Annualised Return	21.84%	21.82%
	Annualised Standard Deviation	21.20%	21.31%
	Risk-Adjusted Return	1.03	1.02
	Average % Cash	47.97%	46.12%
	Annualised Jensen's Alpha	6.30%	6.24%
	Calendar Years Outperformance	21	20
	Calendar Years Underperformance	12	12
	Calendar Years Same Performance	10	12

Sample Period: January 1965 – January 2010. Average Annualised Returns are calculated as average t-period returns over the sample period multiplied by 12/t. The Annualised Standard Deviations are calculated as the standard deviation of returns over the sample period multiplied by the square root of 12/t. Risk-Adjusted Returns are calculated as average annualised return/annualised standard deviation. Annualised Jensen's alpha is calculated as the annualised C in the regression equation: Excess Returns(Trading Strategy) = C + Beta(Excess Returns(JSE ALSI))

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The trading strategy based on the augmented model performs better across all metrics besides standard deviation across all time frames. Apart from 3-month returns, the trading strategy based on the initial model has lower standard deviations. Apart from returns based on a 6-month trading strategy, the trading strategies based on the augmented model also tend to be in a cash position more often than the strategies based on the initial model. As a risk-free asset is expected to generate lower returns than a risky asset, this finding combined with the excess returns realised in all return horizons is counterintuitive. However, if these additional cash positions occur during times when the JSE ALSI is generating negative returns, this strategy will generate additional returns.

To analyse the characteristic of returns through time, the cumulative performance of the trading strategy applied to 1-month returns, chosen as it has the best overall risk-reward characteristics, and 6-month returns, chosen as it has the best absolute reward characteristics, are graphed against the cumulative performance of the ALSI, based to 100 and using a logarithmic axis scale.

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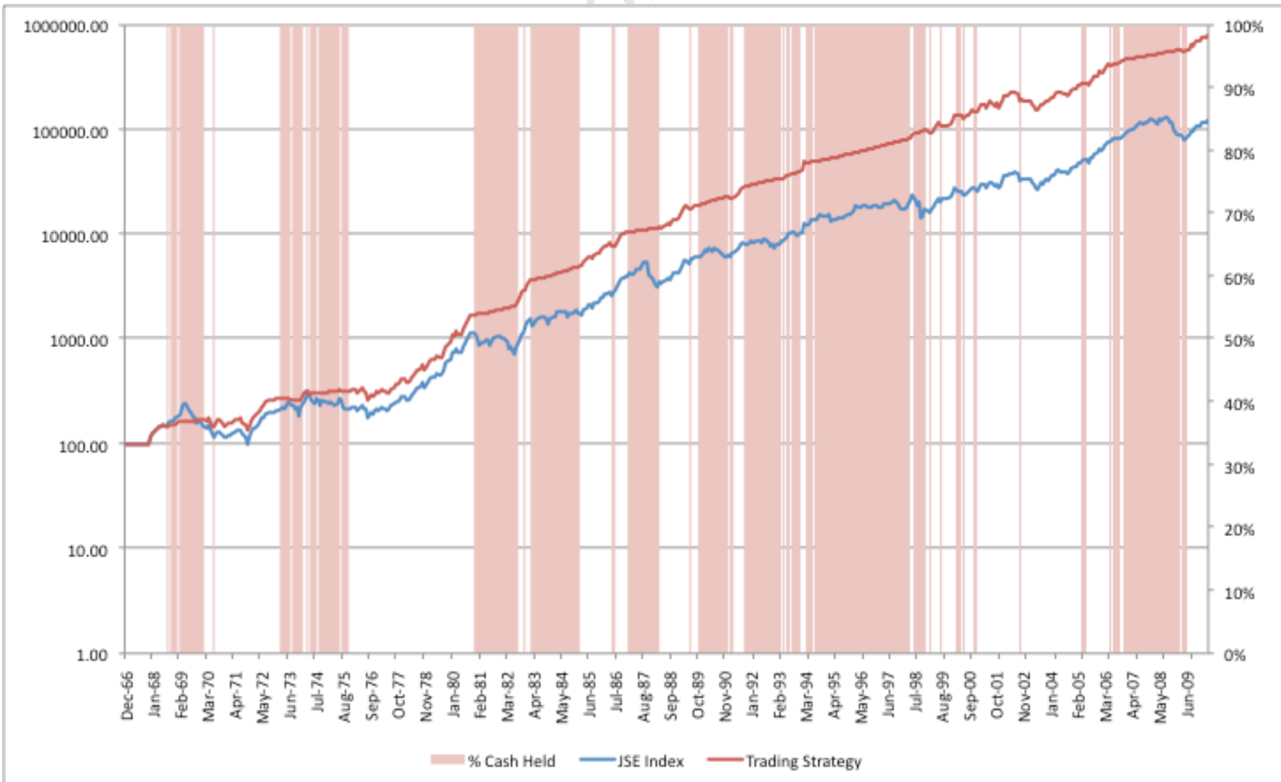
Figure 7.5 Cumulative Value of 1-Month Trading Strategy A relative to the JSE ALSI



For most of 1967-1968, the trading strategy maintains a position in the JSE ALSI and realises the same returns as the index. However, the trading strategy then holds a cash position for most of 1969, yielding lower returns during a period of large returns but yielding higher returns when the stock market then declines sharply. Between 1970-1973, the trading strategy is again invested in the JSE ALSI and follows the same pattern as the index. Through 1973-1975, the trading strategy is invested mostly in the risk-free asset, missing out on a period of large positive returns in 1973 and only earning a return slightly less than that of the JSE ALSI during the flat period between 1974-1975. Between 1975-1981, the trading strategy is again invested in the JSE ALSI, participating in a strong bull period. In the period between 1981-1984, the trading strategy is mostly invested in the risk-free asset, avoiding the negative returns realised in 1982, but correctly switching the strategy to a position in the JSE ALSI during the large positive returns in 1983. Between 1985-1987, the strategy is invested in the JSE ALSI, again participating in a strong bull run. The switch to the risk-free asset in 1988 caused the trading strategy to not participate in the very strong run-up to the 1988 crash; however, it also misses this crash and therefore ends the period in a better position relative to the JSE ALSI. For 1988-1989, the trading strategy is mostly invested in the JSE ALSI, participating in strong stock market returns. Between 1990-1998, the strategy is mostly invested in the JSE ALSI and does not participate in the slightly higher JSE ALSI returns, but avoiding any sharp declines. From 1998-2007, the trading strategy is invested in the JSE ALSI, participating in the majority of excess positive returns. However, it doesn't switch to the risk-free asset during the crisis resulting from the Asian and Russian Financial Crises and it is also negatively affected by the events. Between 2007-2009, the trading strategy is mostly invested in the risk-free asset, missing the returns at the top of the bull-run but also avoiding the sharp declines resulting from the sub-prime crisis. From 2009, the trading strategy has been invested in the JSE ALSI and has realised the returns that have resulted from the recovery from the sub-prime crisis.

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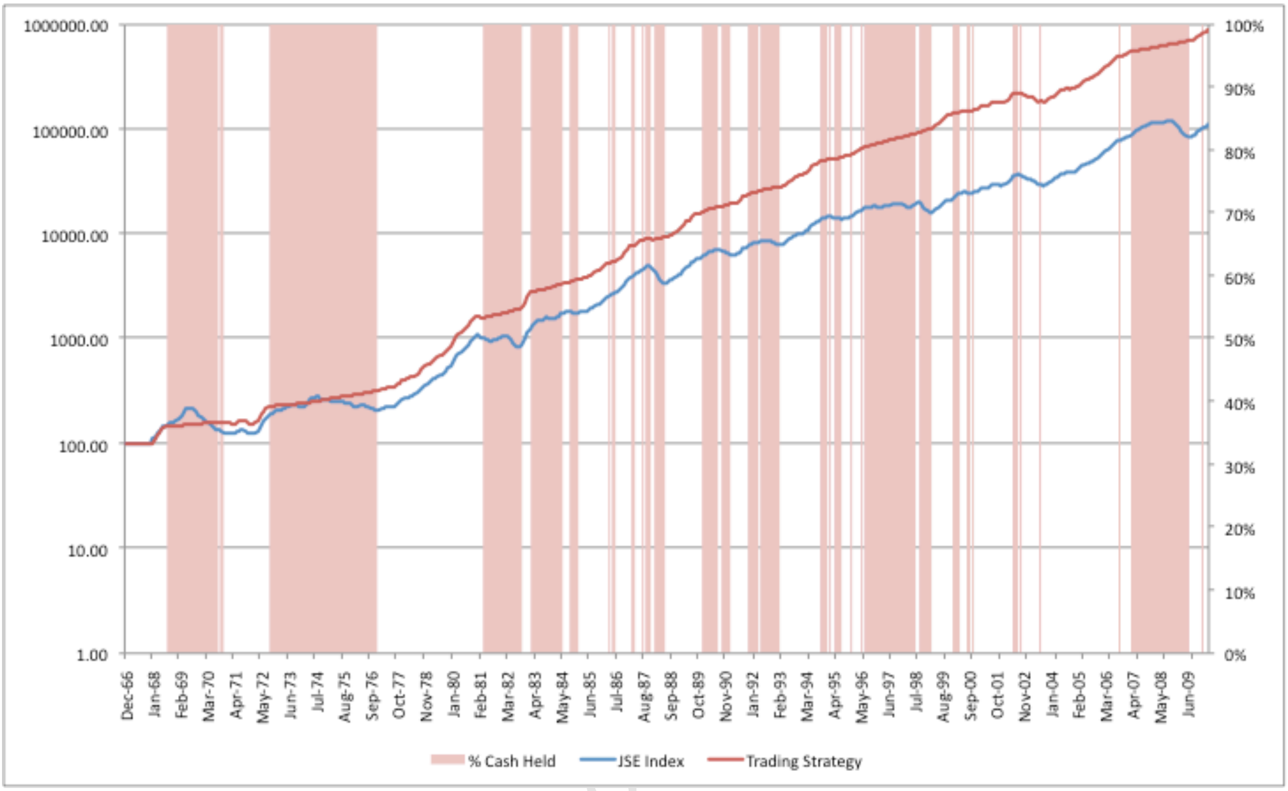
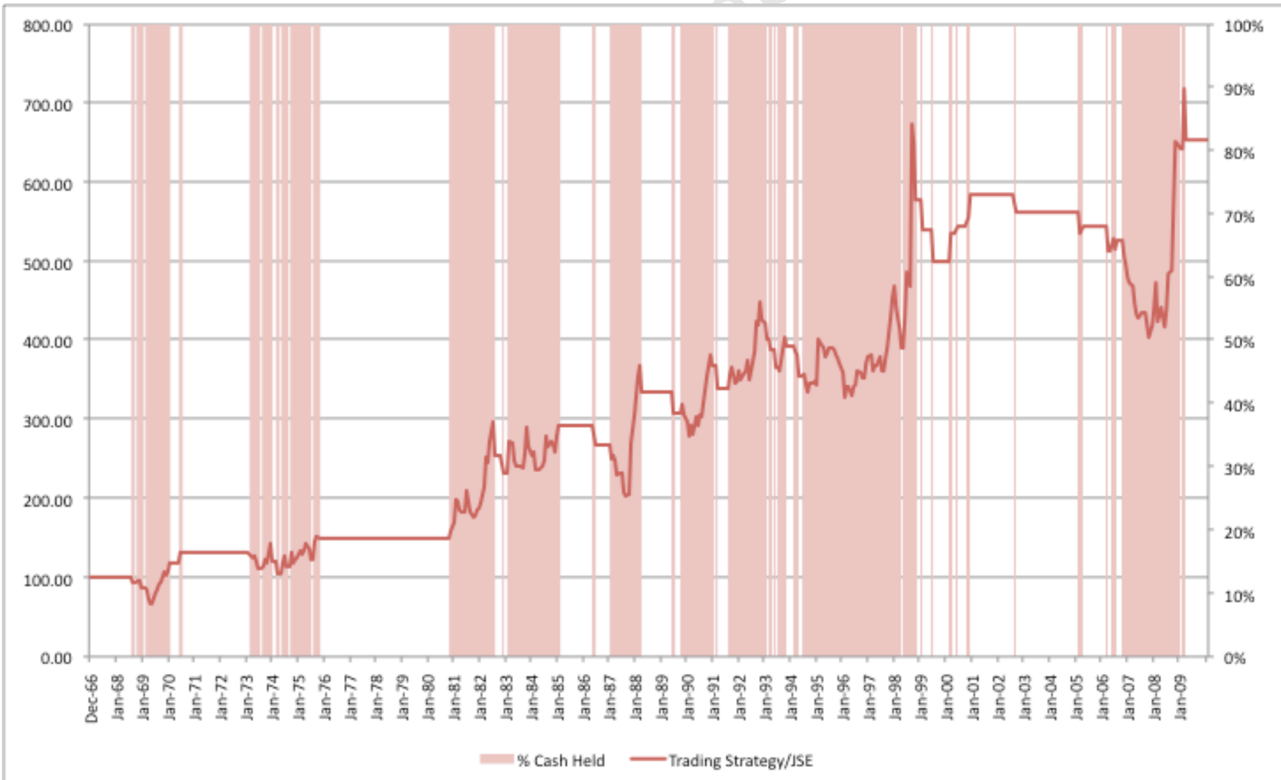
Figure 7.6 Cumulative Value of 6-Month Trading Strategy A relative to the JSE ALSI



For 1967-1968, the trading strategy maintained a position in the JSE ALSI and matched the index. However, the trading strategy then held a cash position for most of 1969-1970, yielding lower returns during a strong bull period but yielding higher returns when the stock market dropped dramatically after its build-up. Between 1971-1973, the trading strategy is again invested in the JSE ALSI and follows the same pattern as the index. Through 1973-1977, the trading strategy is invested mostly in the risk-free asset, missing out on a period of large positive returns in 1973 and earning a return slightly less than that of the JSE during the flat period between 1974-1975 and outperforming between 1975-1976. Between 1976-1981, the trading strategy is again invested in the JSE ALSI, participating in a strong bull period. In the period between 1981-1984, the trading strategy is mostly invested in the risk-free asset, avoiding the negative returns realised in 1982, but correctly switching the strategy to investment in the JSE ALSI in 1983 when there is a sharp positive increase. Between 1985-1997, the trading strategy is mostly invested in the JSE ALSI and realises most of the positive returns over that time period while switching to a risk-free position slightly before sharp declines in the index. Between 1996-1998, the strategy is invested in the risk-free asset and realises returns in excess of the poor performance of the JSE ALSI over the time period. Between 1999-2007, the trading strategy is invested in the JSE ALSI, participating in the majority of excess positive returns. However, it doesn't switch to the risk-free asset during the crisis resulting from the Asian and Russian Financial Crises and it is also negatively affected by the events. Between 2007-2009, the trading strategy is mostly invested in the risk-free asset, missing the returns at the top of the bull-run but also avoiding the sharp declines resulting from the sub-prime crisis. From 2009, the trading strategy has been mostly invested in the JSE ALSI and has realised the returns that have resulted from the recovery post-sub-prime crisis.

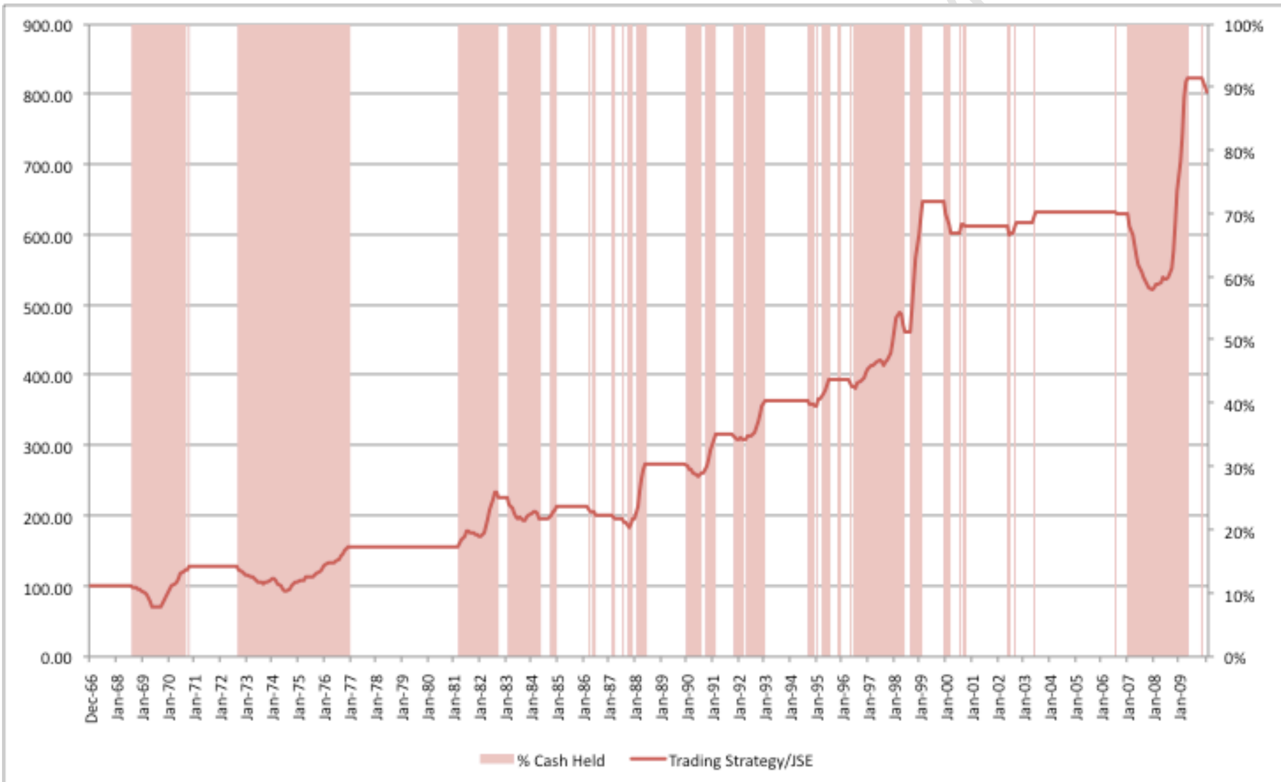
An analysis of indices provides a visual aid to determine periods of positive and negative returns, but to more accurately compare the characteristics of outperformance, the graphs below shows the value of the cumulative strategy values relative to the cumulative ALSI value.

Figure 7.7 Cumulative Outperformance of 1-Month Trading Strategy A relative to JSE ALSI



As the portfolio holds either a risk-free asset or the JSE ALSI, the pattern of outperformance relative to the JSE ALSI occurs in periods where the risk-free asset is held in lieu of the JSE ALSI when the JSE ALSI declines. In most of these holding periods, the trading strategy initially underperforms relative to the JSE ALSI before the underperformance is reversed and a positive relative return is made overall over the holding period. This suggests that the augmented forecast model is predicting the value of the JSE ALSI and moves the strategy position away from the JSE ALSI when the index is highly overvalued. However, there are also periods, notably in the 1990s, when the trading strategy either incorrectly times a decline in the market and underperforms the market or retains a risk-free asset position for too long and loses some of the outperformance earned during after a decline in the JSE ALSI.

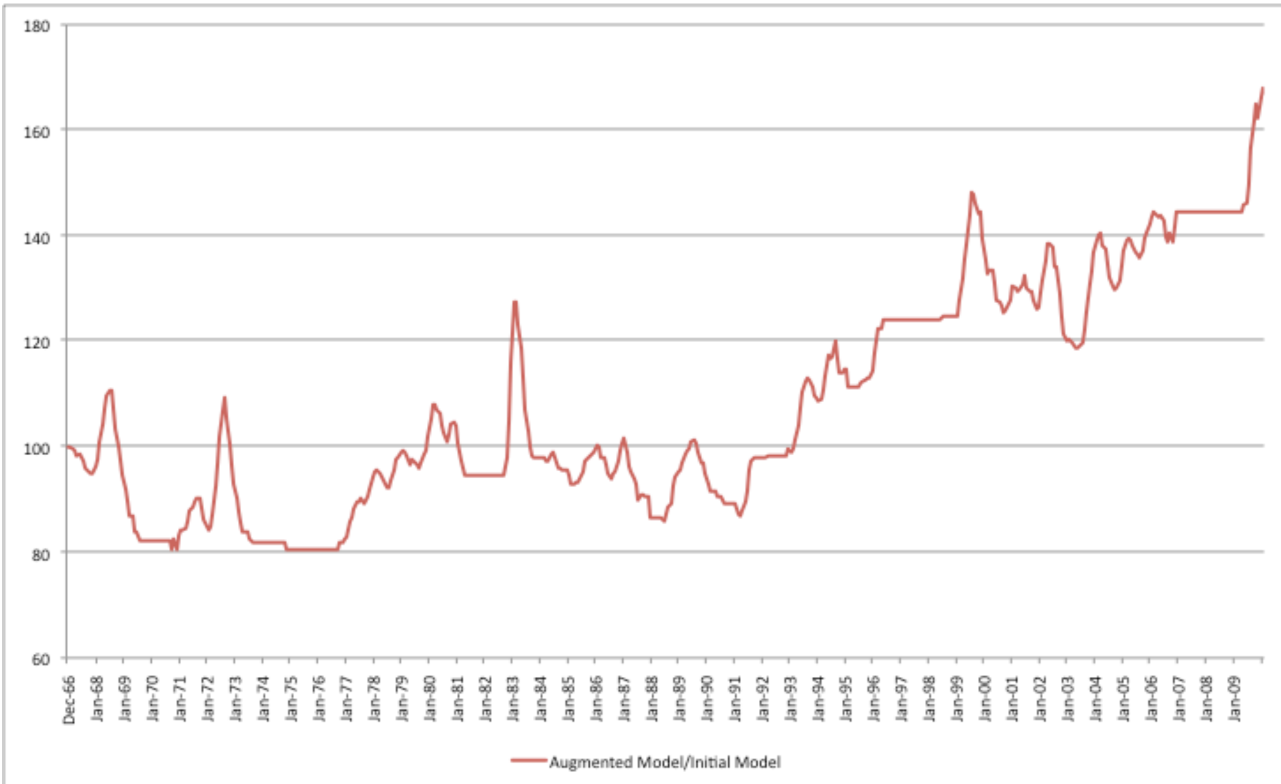
Figure 7.8 Cumulative Outperformance of 6-Month Trading Strategy A relative to JSE ALSI



The pattern of outperformance for 6-month returns is very similar for 1-month returns. However, the initial period of underperformance in 6-month returns tend to be either shorter than the equivalent 1-month returns or to not occur at all, with the exception to the run-up to the sub-prime crisis in 2007-2008. There are also less incorrect calls of a decline in the JSE ALSI throughout the time period. It is a combination of these two findings that causes the 6-month based trading strategy to outperform the 1-month trading strategy, in absolute terms, over the sample period.

Finally, to compare the performance of the trading strategies based on the two forecast models, the relative value of the highest yielding return horizon of the augmented model based trading strategy A (6-months) against the highest yielding return horizon of the initial model based trading strategy A (12-months).

Figure 7.9 Cumulative Outperformance of 6-Month Augmented Forecast model Trading Strategy A Performance relative to 12-Month Inital Forecast model Trading Strategy A



The trading strategy based on the initial model outperforms the trading strategy based on the augmented model for most of the period between 1966-1974, with the exception of two sharp periods of outperformance that are quickly reversed. For 1975-1979, the augmented model based trading strategy outperforms the initial model based trading strategy. However, both trading strategies remain flat until early 1993. From this period on, the trading strategy based on the augmented model outperforms the trading strategy based on the initial model by approximately 60% over the time period.

This figure indicates that although the augmented predicted model is the best generator of returns over the entire sample, there is a period of several years at the beginning of the sample where the initial model provides superior forecasts compared to the augmented model.

Trading Strategy B

Like Trading Strategy A, the optimal return horizon depends on the choice of performance metric. A 12-month return horizon has the greatest absolute return (19.22%) and the largest Jensen's alpha (3.76%), while 1-month returns have the highest risk-adjusted return (1.5) and lowest annualised standard deviation (11.21%) and 3-month returns have the most years of calendar outperformance (24). Unlike trading strategy A, there is a clear trend of the average percentage cash held, with longer return horizons holding a smaller average cash position (which is possibly why longer return horizons have larger standard deviations).

Irrespective of return horizon, trading strategy B provides lower standard deviations, higher risk-adjusted returns and a positive Jensen's alpha and, with the exception of 1-month returns, a higher absolute average return relative to the JSE ALSI. Compared to trading strategy A, trading strategy B provides lower standard deviations and higher risk-adjusted returns and Jensen's alpha across all return horizons, but lower absolute returns. As the construction of this trading strategy requires a position to be held in a risk-free asset and the risky asset, this finding is not surprising.

To compare the performance of trading strategy B based on the forecasts of the augmented model relative to the initial model, the metrics of both are tabulated below.

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Table 7.9 Comparison of Trading Strategy B from Augmented Model relative to Initial Model

		Augmented Model	Initial Model
1-Month	Average Annualised Return	16.79%	16.13%
	Annualised Standard Deviation	11.21%	11.03%
	Risk-Adjusted Return	1.50	1.46
	Average % Cash	49.06%	49.31%
	Annualised Jensen's Alpha	1.64%	1.30%
	Calendar Years Outperformance	20	21
	Calendar Years Underperformance	23	23
	Calendar Years Same Performance	0	0
3-Month	Average Annualised Return	17.93%	16.83%
	Annualised Standard Deviation	12.81%	12.32%
	Risk-Adjusted Return	1.40	1.37
	Average % Cash	48.59%	48.97%
	Annualised Jensen's Alpha	2.53%	1.84%
	Calendar Years Outperformance	24	23
	Calendar Years Underperformance	19	21
	Calendar Years Same Performance	0	0
6-Month	Average Annualised Return	19.20%	17.51%
	Annualised Standard Deviation	14.53%	13.66%
	Risk-Adjusted Return	1.32	1.28
	Average % Cash	48.49%	48.74%
	Annualised Jensen's Alpha	3.71%	2.38%
	Calendar Years Outperformance	19	20
	Calendar Years Underperformance	24	24
	Calendar Years Same Performance	0	0

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Table 7.9 Comparison of Trading Strategy B from Augmented Model relative to Initial Model

12-Month	Average Annualised Return	19.22%	19.05%
	Annualised Standard Deviation	17.15%	17.31%
	Risk-Adjusted Return	1.12	1.10
	Average % Cash	48.43%	48.26%
	Annualised Jensen's Alpha	3.76%	3.63%
	Calendar Years Outperformance	20	20
	Calendar Years Underperformance	23	24
	Calendar Years Same Performance	0	0

Sample Period: January 1965 – January 2010. Average Annualised Returns are calculated as average t-period returns over the sample period multiplied by 12/t. The Annualised Standard Deviations are calculated as the standard deviation of returns over the sample period multiplied by the square root of 12/t. Risk-Adjusted Returns are calculated as average annualised return/annualised standard deviation. Annualised Jensen's alpha is calculated as the annualised C in the regression equation: Excess Returns(Trading Strategy) = C + Beta(Excess Returns(JSE ALSI))

Irrespective of return horizon, the strategy based off the augmented model's forecasts has higher absolute average annualised returns, higher risk-adjusted returns and higher Jensen's alphas than the corresponding return horizon of the strategy based off the initial model's forecasts. 1 and 6-month return horizons have fewer calendar years of outperformance using the augmented model's forecasts, while 3-months returns have one year more and 12-month returns have the same amount. Standard deviations are also higher in the strategies based off the augmented model with the exception of a 12-month return horizon.

To analyse the characteristic of returns through time, the cumulative performance of the trading strategy applied to 1-month returns, chosen as it has the best overall risk-reward characteristics, and 12-month returns, chosen as it has the best absolute reward characteristics, are graphed against the cumulative performance of the ALSI, based to 100 and using a logarithmic axis scale.

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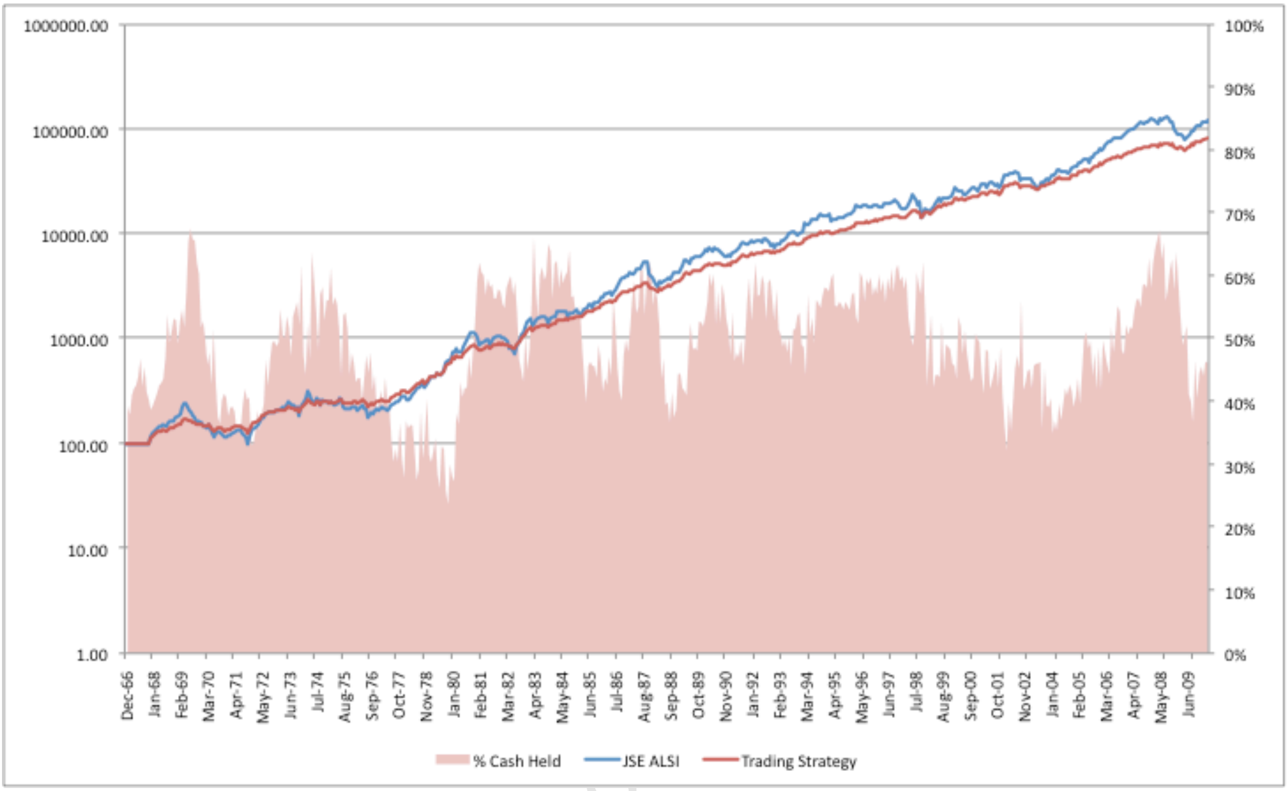
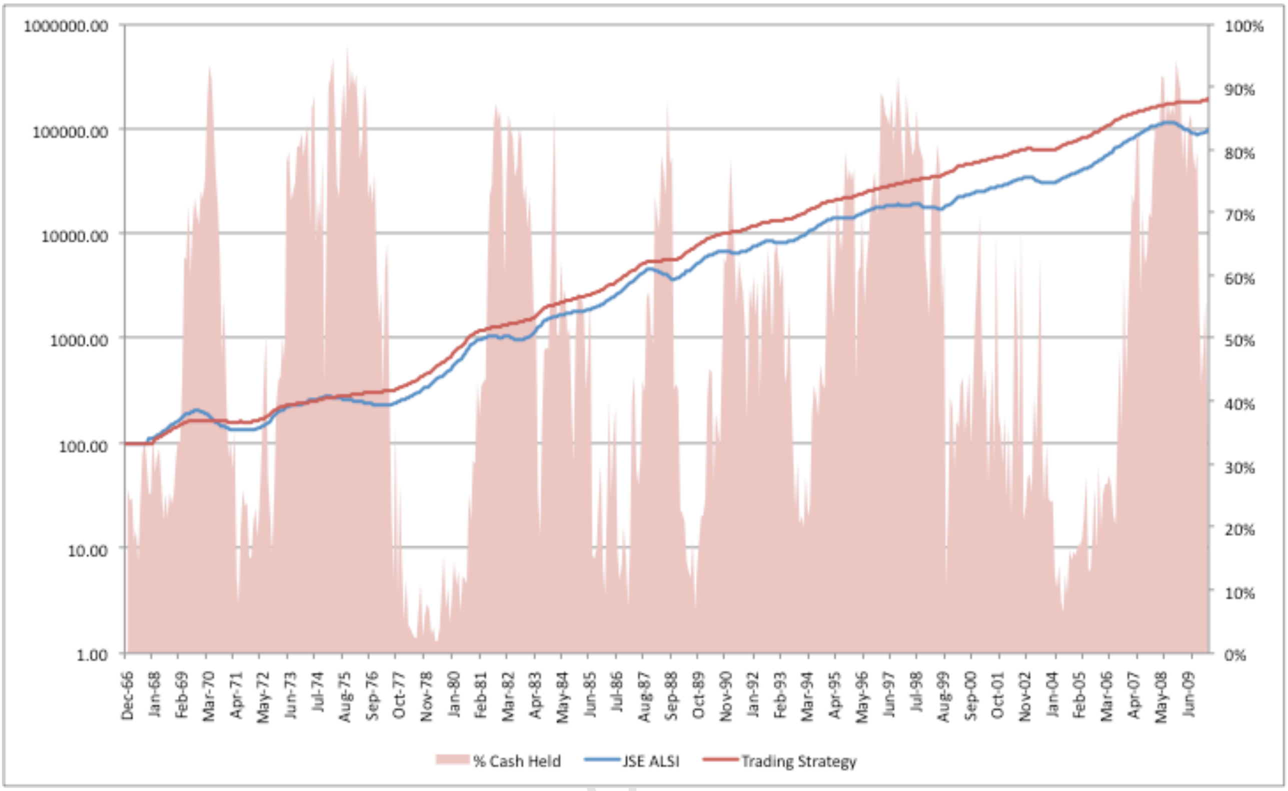
Figure 7.10 Cumulative Value of 1-Month Trading Strategy B relative to the JSE ALSI



For the majority of the period between 1967 to early 1979, the trading strategy has a value in excess of the value of the JSE ALSI. However, from that period onwards, the JSE ALSI has a higher cumulative value, with the exception of several months in 1982, caused by a sharp market decline stemming from a sharp drop in commodity prices, and one month in 1998, which occurs as a result of the sharp market decline stemming from the Asian and the Russian Financial Crises. Throughout the sample period, the trading strategy has followed a trend that has a pattern similar to that of the JSE ALSI, but with less volatility. Thus, when the JSE ALSI increases, the trading strategy also increases, but by a lesser degree, and follows the JSE ALSI during a decline, but also by a smaller absolute magnitude. This is as a result of the portfolio construction, which requires positions to be held in both the risky and the risk-free asset, and the spread of probability values clustering narrowly around 50%, thereby preventing the strategy from holding very aggressive positions in either of the asset classes.

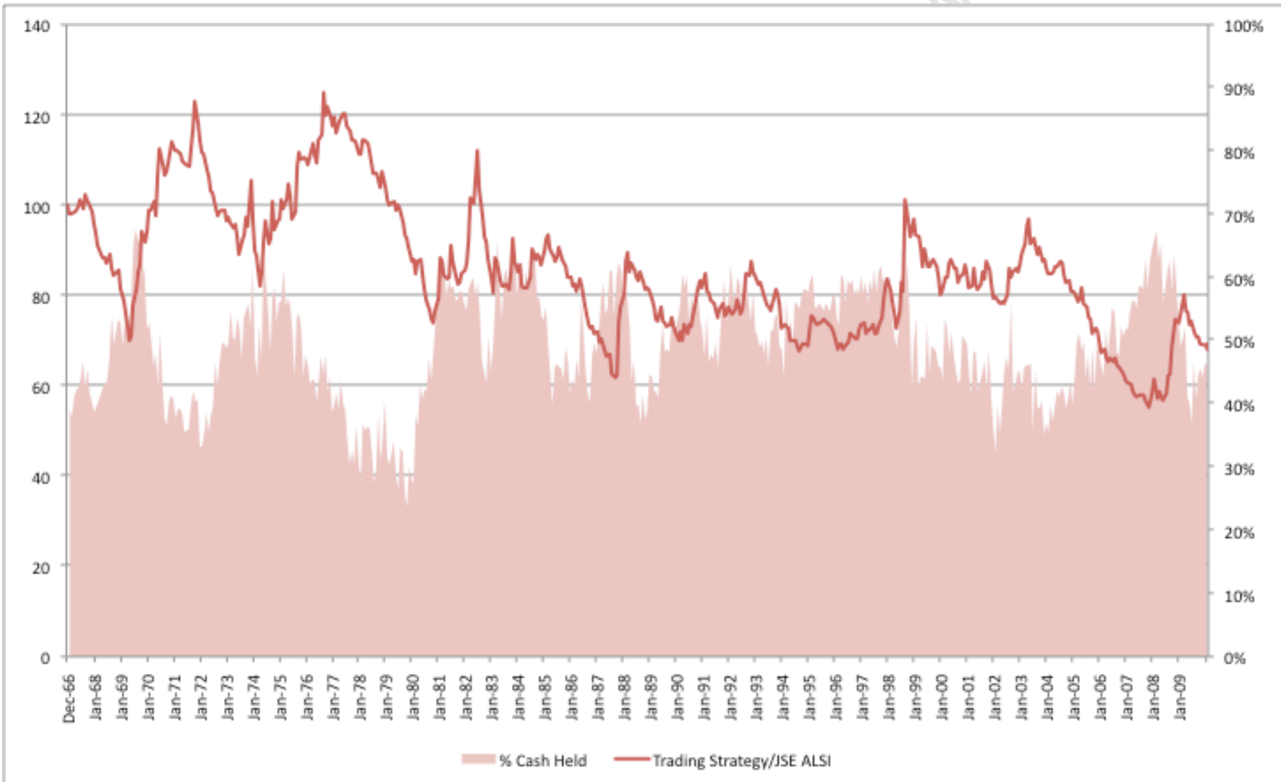
Figure 7.11 Cumulative Value of 12-Month Trading Strategy B relative to the JSE ALSI



The trading strategy initially underperforms relative to the JSE ALSI until midway through 1970, when the cumulative value of the trading strategy exceeds that of the JSE ALSI for the first time. Following a period of strong growth in the JSE ALSI from 1970 to 1972, the value of the JSE ALSI slightly exceeds that of the trading strategy for a period of several months, as the trading strategy moves to a relatively small position in the JSE ALSI. The trading strategy maintains this position and therefore, unlike the JSE ALSI, does not generate negative returns from 1975 to 1977. During the next 5 years of strong JSE ALSI performance, the trading strategy loses some of its gains as it is held back by a small risk-free asset position. However, a shift to a larger position in the risk-free asset in 1981 allows the strategy to continue generating a positive return during a period of slight decline for the JSE ALSI. From 1983-1987, the trading strategy and the JSE ALSI grow at a similar rate. In early 1988, there are large, positive movements in the JSE ALSI, and the difference between the value of the strategy and the JSE ALSI declines. However, during the Black Monday crash in October 1988, the trading strategy grows slightly while the JSE ALSI declines sharply. From 1989 to 2005, the trading strategy and the JSE ALSI grow at a similar rate, with the strategy generating similar returns with lower volatility. In the build-up to the sub-prime crisis, the trading strategy, while still generating positive returns, grows at a slower rate compared to the JSE ALSI. However, the movement to a risk-free asset dominated strategy from 2006 onwards protects the strategy from the sharp downturn in 2008.

An analysis of indices provides a visual aid to determine periods of positive and negative returns, but to more accurately compare the characteristics of outperformance, the graphs below shows the value of the cumulative strategy values relative to the cumulative ALSI value.

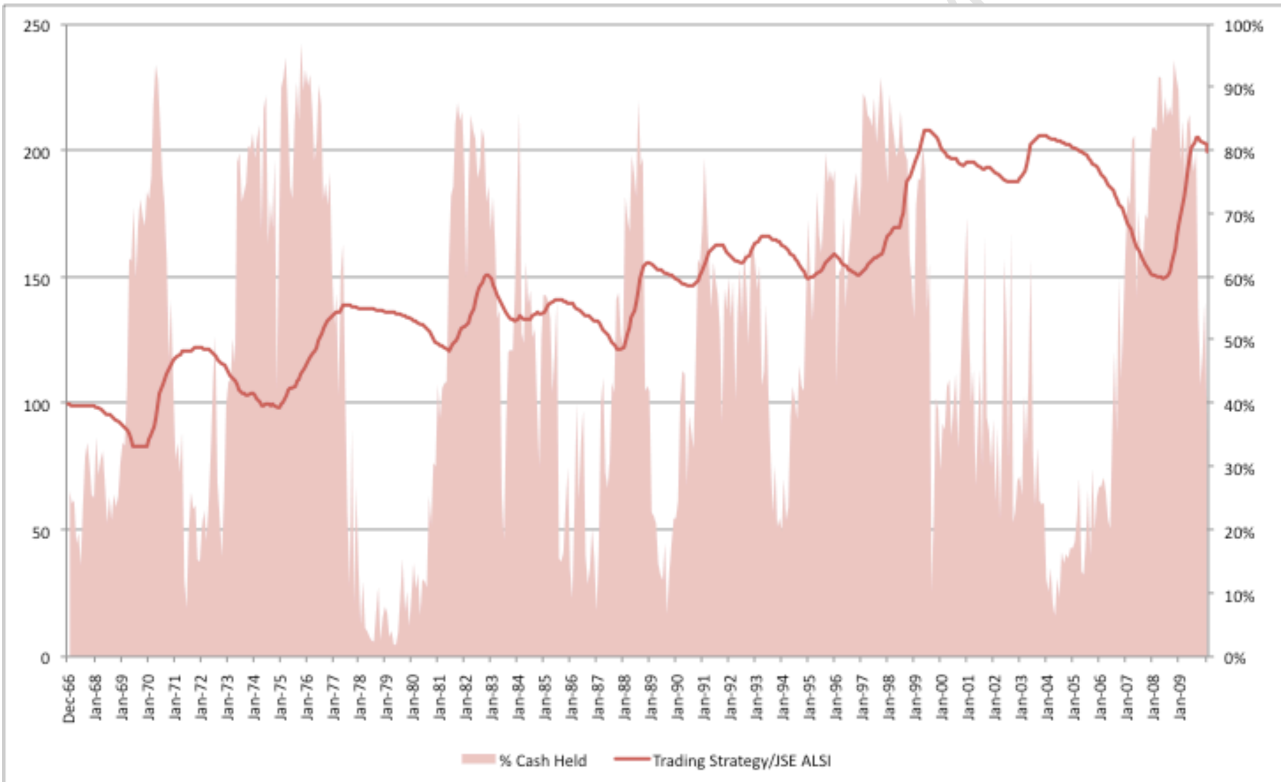
Figure 7.12 Cumulative Outperformance of 1-Month Trading Strategy B relative to JSE ALSI



The graph of cumulative outperformance indicates the pattern of underperformance of the trading strategy relative to the JSE ALSI. From 1967 to 1982, the strategy and the JSE ALSI generate approximately the same returns, with outperformance by one matched in the following period by outperformance by the other. However, there is strong growth after 1982 in the JSE ALSI, which is not followed by a sharp market decline. As such, the trading strategy fluctuates at roughly 80% the value of the JSE ALSI, until 1998. Due to the negative contagion caused by the Asian and Russian financial crises, the trading strategy sharply outperforms the JSE

ALSI, temporarily exceeding the value of the JSE ALSI. The strong commodity run that follows causes the strategy to underperform, before outperforming sharply as the market corrects. However, the strategy is not invested heavily enough in the JSE ALSI to participate in the strong growth in the JSE ALSI after 2003, and loses roughly 40% of its value relative to the JSE ALSI. The declines in ALSI due to the sub-prime crisis restores some of this relative loss in valuation, but the strategy once again loses relative value as the market recovered from its decline.

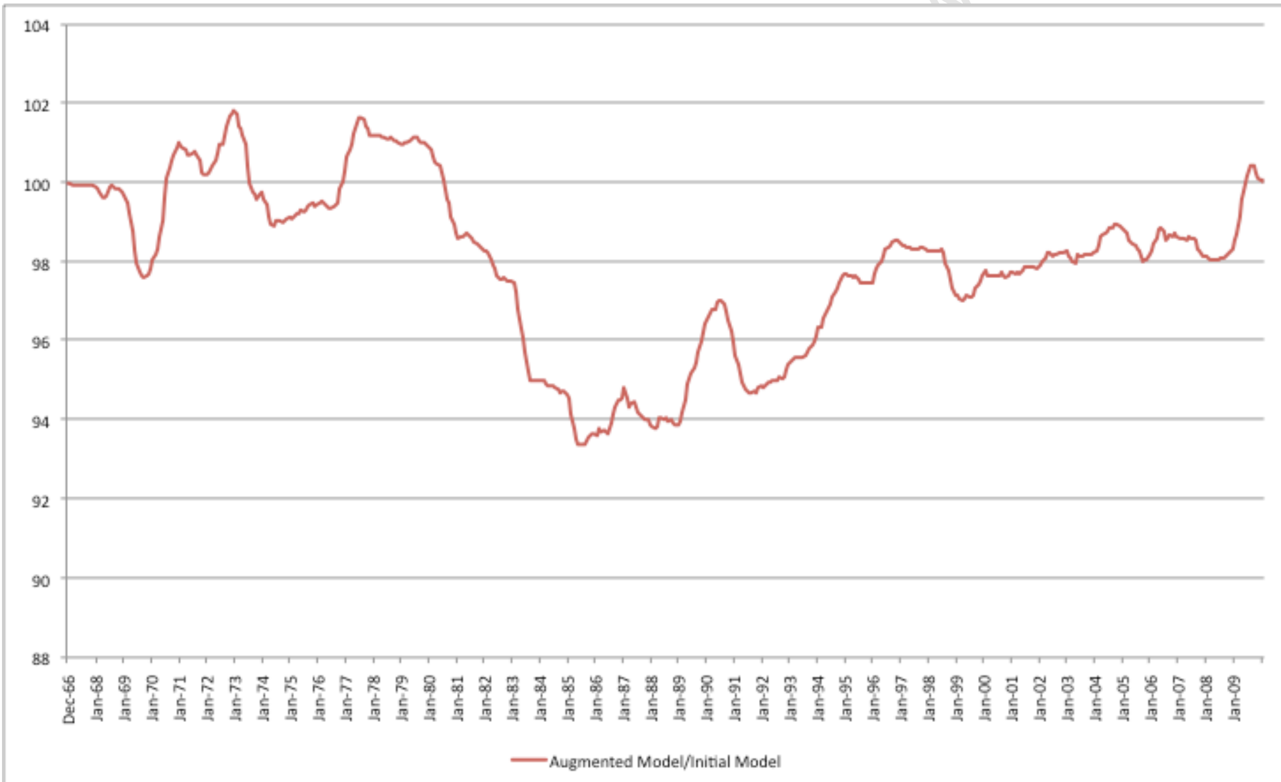
Figure 7.13 Cumulative Outperformance of 12-Month Trading Strategy B relative to JSE ALSI



The pattern of outperformance for a 12-month return horizon of trading strategy B is clear from the figure above. During periods of strong JSE ALSI returns, the strategy is unable to fully participate in the gains as it still holds a portion of the portfolio in the risk-free asset, and as such, it underperforms relative to the JSE ALSI. It also occasionally switches to a cash-heavy position several periods before a negative return in the market, and as such, it does not realise the returns at the top of a strong upward run in the JSE ALSI. However, when the run ceases and the market declines sharply, the trading strategy retains its value while the JSE ALSI loses its value, and these are the occasions where the strategy strongly outperforms the JSE ALSI.

Finally, to compare the performance of the trading strategies based on the two forecast models, the relative value of the highest yielding return horizon of the augmented model based trading strategy B (12-months) against the highest yielding return horizon of the initial model based trading strategy B (12-months).

Figure 7.14 Cumulative Outperformance of 12-Month Augmented Forecast model Trading Strategy B Performance relative to 12-Month Inital Forecast model Trading Strategy B



The performance of the 12-month trading strategy using the different models is fairly similar, with the cumulative returns of both strategies staying within a range of 7% of each other. However, there are different periods of performance of the two strategies. From 1967 to 1981, the two models' strategies are fairly similar, with outperformance in one followed by outperformance in the other. From 1982 to 1986, there is a sharp relative underperformance by the augmented model's trading strategy. From 1986 to 2008, the augmented model's trading strategy consistently slightly outperforms the initial model's trading strategy. However, in 2008, the augmented model's trading strategy substantially outperforms relative to the initial model's trading strategy, although this outperformance appears to be reversing marginally in the period in 2009.

The figure above indicates that the initial and augmented models' forecasts provide similar returns over the same sample but significantly different returns in certain timeframes within the sample. This implies that despite the evidence that the augmented model is a superior predictor of excess returns, this does not translate into constant superior returns in this trading strategy.

Trading Strategy C

Like trading strategy B, the optimal choice in return horizon is dependent on the performance metric chosen. 12-month returns have the highest absolute average annualised returns (19.50%) and the highest Jensen's alpha (7.52%), while 1-month returns have the highest risk-adjusted return (3.53) and the lowest annualised standard deviation (4.03%) and 3-month returns have the greatest calendar years of outperformance (22). There is also a clear trend in the average risk-free asset position, with it decreasing from 98.11% for 1-month returns to 96.86% for 12-month returns.

Trading strategy C yields greater risk-adjusted returns, Jensen's alphas and lower annualised standard deviations across return horizons relative to a respective buy-and-hold strategy in the JSE ALSI. However, the strategy yields lower average annualised returns for 1 and 3-month returns (14.23% against 17.80% and 16.33% against 17.79% respectively). A 6-month return horizon and a 12-month return horizon yield an excess average annualised return of over 1% and 2% respectively against a pure buy-and-hold strategy in the JSE ALSI. The trading strategy also provides a higher risk-adjusted return and Jensen's alpha and a lower standard deviation compared to trading strategy A and B, holding the return horizon constant. However, with the exception of 12-month returns, the absolute average annualised return is lower for trading strategy C compared to respective return horizons of trading strategy B, and lower than any absolute average annualised return generated by trading strategy A.

To determine the performance of the augmented model relative to the initial model, the two strategies, constructed from each models' forecasts, are tabulated below.

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Table 7.10 Comparison of Trading Strategy C from Augmented Model relative to Initial Model

		Augmented Model	Initial Model
1-Month	Average Annualised Return	14.23%	13.27%
	Annualised Standard Deviation	4.03%	3.48%
	Risk-Adjusted Return	3.53	3.81
	Average % Cash	98.11%	98.62%
	Annualised Jensen's Alpha	3.31%	2.62%
	Calendar Years Outperformance	19	18
	Calendar Years Underperformance	24	26
	Calendar Years Same Performance	0	0
3-Month	Average Annualised Return	16.33%	14.51%
	Annualised Standard Deviation	7.03%	5.80%
	Risk-Adjusted Return	2.32	2.5
	Average % Cash	97.17%	97.94%
	Annualised Jensen's Alpha	5.12%	3.71%
	Calendar Years Outperformance	22	22
	Calendar Years Underperformance	21	22
	Calendar Years Same Performance	0	0
6-Month	Average Annualised Return	18.79%	15.80%
	Annualised Standard Deviation	11.24%	8.40%
	Risk-Adjusted Return	1.67	1.88
	Average % Cash	96.98%	97.48%
	Annualised Jensen's Alpha	7.49%	4.79%
	Calendar Years Outperformance	19	17
	Calendar Years Underperformance	24	27
	Calendar Years Same Performance	0	0

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Table 7.10 Comparison of Trading Strategy C from Augmented Model relative to Initial Model

12-Month	Average Annualised Return	19.50%	19.36%
	Annualised Standard Deviation	14.34%	14.32%
	Risk-Adjusted Return	1.36	1.35
	Average % Cash	96.86%	96.53%
	Annualised Jensen's Alpha	7.52%	7.26%
	Calendar Years Outperformance	20	20
	Calendar Years Underperformance	23	24
	Calendar Years Same Performance	0	0

Sample Period: January 1965 – January 2010. Average Annualised Returns are calculated as average t-period returns over the sample period multiplied by 12/t. The Annualised Standard Deviations are calculated as the standard deviation of returns over the sample period multiplied by the square root of 12/t. Risk-Adjusted Returns are calculated as average annualised return/annualised standard deviation. Annualised Jensen's alpha is calculated as the annualised C in the regression equation: Excess Returns(Trading Strategy) = C + Beta(Excess Returns(JSE ALSI))

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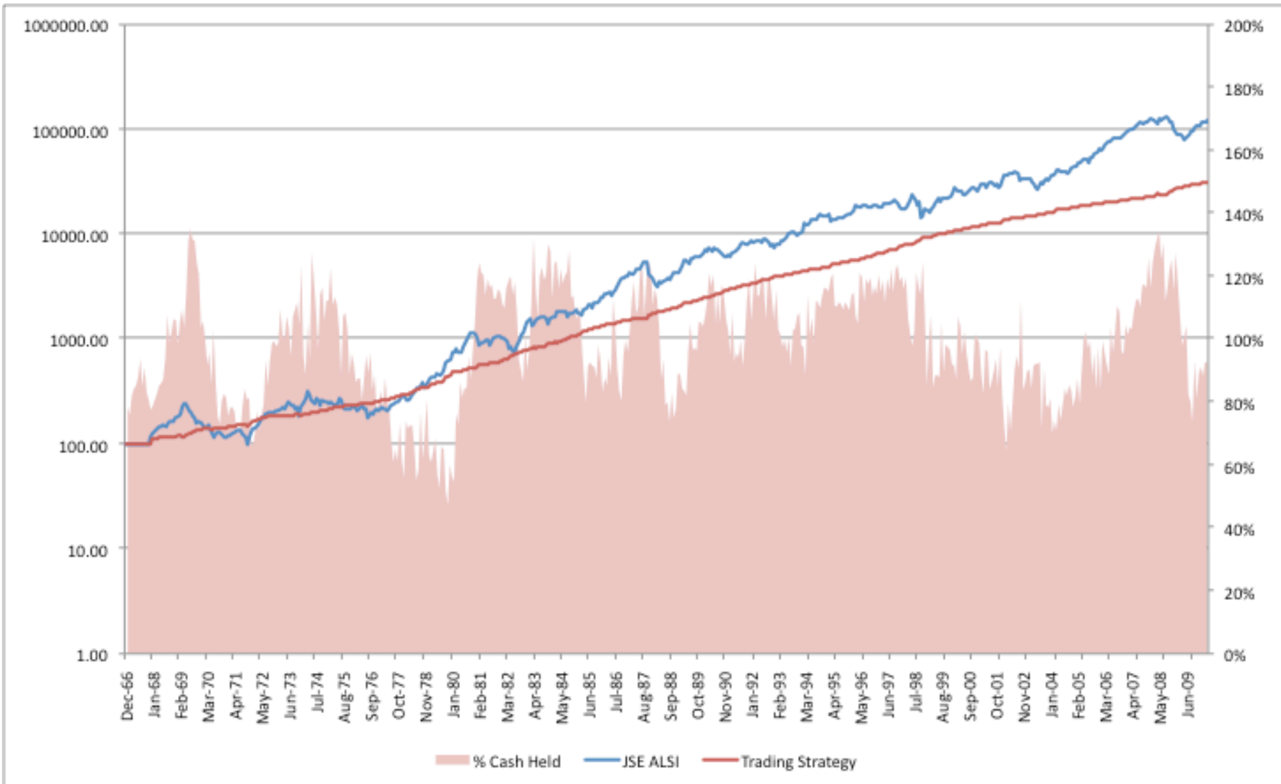
The augmented model provides superior performance, holding return horizon constant, over the initial model in the average annualised return and the annualised Jensen's alpha. This effect is largest for a 6-month return horizon, where the augmented model based strategy generates returns in excess of slightly under 3% and a Jensen's alpha 2.7% greater than the metrics generated by the initial model. However, the excess returns are generated with a higher standard deviation and therefore, with the exception of a 12-month return horizons, the trading strategy based off the initial model provides a superior risk-adjusted return compared to the trading strategy based off the augmented model. Therefore, unlike the previous two strategies, the evidence does not clearly suggest one forecast model is superior to the other, with the choice in model dependent on the criteria needed for return generation.

To analyse the characteristic of returns through time, the cumulative performance of the trading strategy applied to 1-month returns, chosen as it has the best overall risk-reward characteristics, and 12-month returns, chosen as it has the best absolute reward characteristics, are graphed against the cumulative performance of the ALSI, based to 100 and using a logarithmic axis scale.

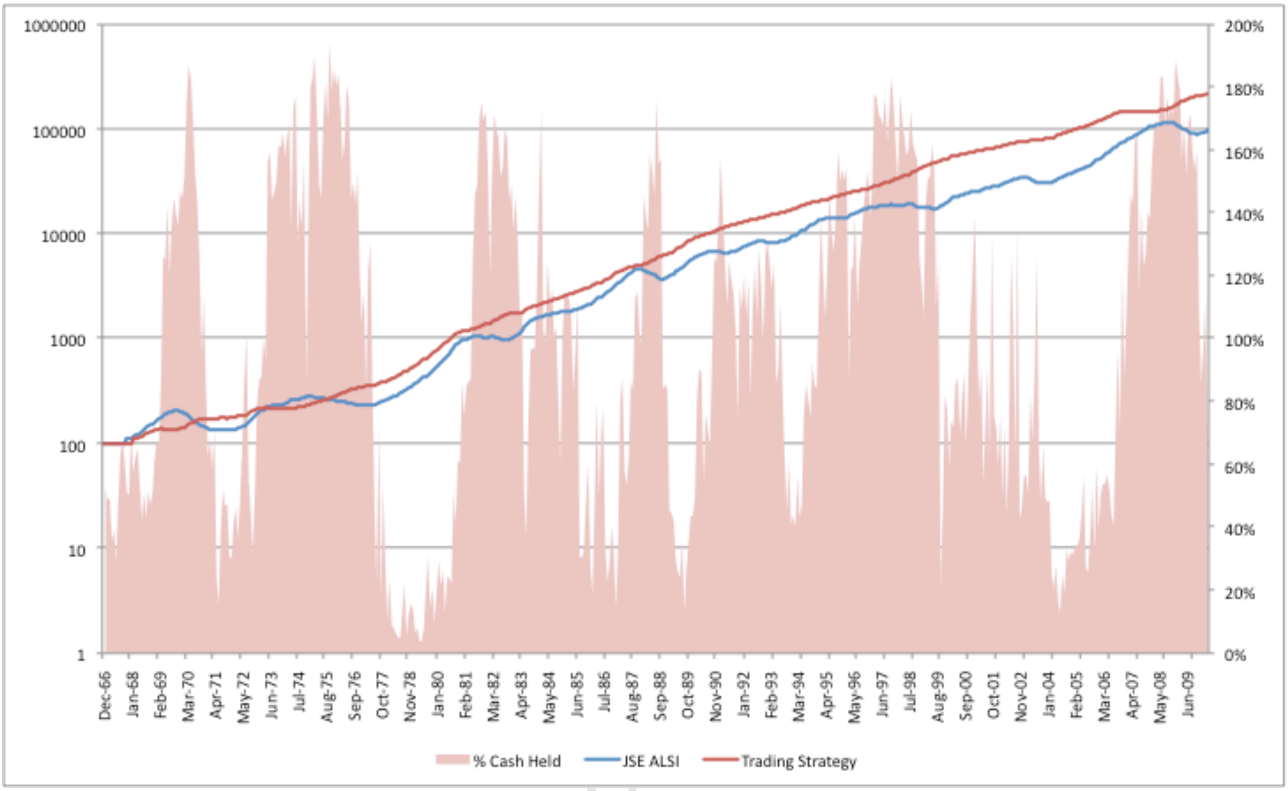
Figure 7.15 Cumulative Value of 1-Month Trading Strategy C relative to the JSE ALSI



A brief visual analysis shows that the 1-month return horizon of this trading strategy adds value with less volatility than that of the JSE ALSI throughout the sample. This is caused primarily by the strategy's large cash positions, with a minimum of just below 60% and a maximum of just below 140%. Thus the strategy is always invested in large cash positions, with very little variation around a full cash position.

Therefore, the strategy does not take large long or short positions on the JSE ALSI. As a result, it can only have minor participation in an increase in the index, when it is in a long position, or a decrease in the index, when it is in a short position. As the JSE, on average, has a return in excess of the risk-free asset, this means that when there are upward trends in the market, the trading strategy is not able to keep pace with the JSE ALSI. When the market declines, the trading strategy still earns positive returns; however, these positive returns are not large enough to reverse the cumulative underperformance that the strategy has earned prior to the market decline. Therefore, a clear pattern of underperformance is visible in the strategy after 1978, when the JSE ALSI began to grow at a faster rate.

Figure 7.16 Cumulative Value of 12-Month Trading Strategy C relative to the JSE ALSI

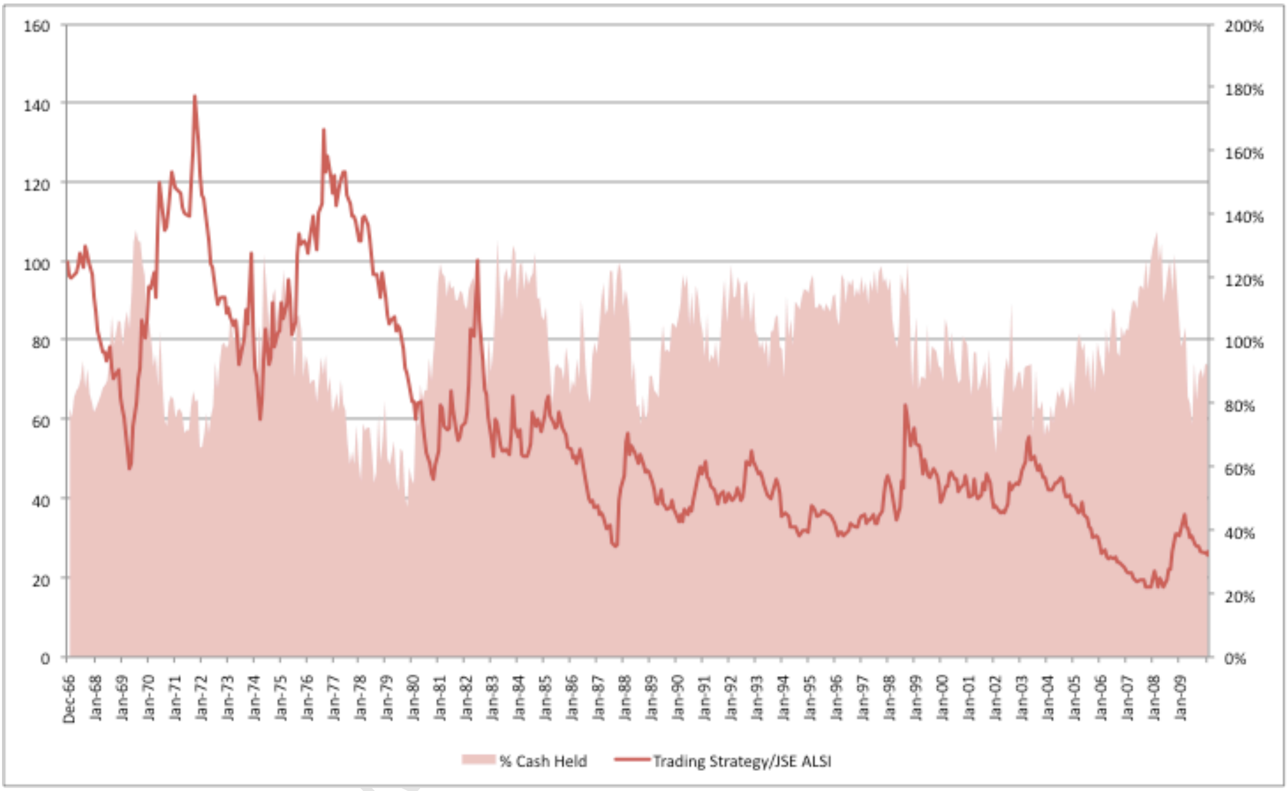


Like 1-month returns, 12-month returns visually appear to yield a less volatile pattern of returns compared to the JSE ALSI. However, there appears to be greater volatility in returns compared to a 1-month trading strategy that is compensated with larger returns as the strategy has a clear pattern of outperformance compared to the JSE ALSI. This is as a result of a larger spread of probabilities of outperformance, meaning that the portfolio generally holds large positions in one of the two asset classes, whereas a 1-month trading strategy holds most of its portfolio in a risk-free asset and a relatively smaller long or short position in the JSE ALSI.

Like trading strategy B, the pattern of returns indicates that the strategy gains value relative to the JSE ALSI during periods when the index is decreasing in value and loses value relative to the JSE ALSI when the index is increasing. However, this increase in relative value is larger than those gained by trading strategy B, as the strategy not only generates returns from a risk-free return during the period, but also gains additional returns by holding a short position in the JSE ALSI. However, when the forecasts are incorrect, it means that there is a larger relative decline in value.

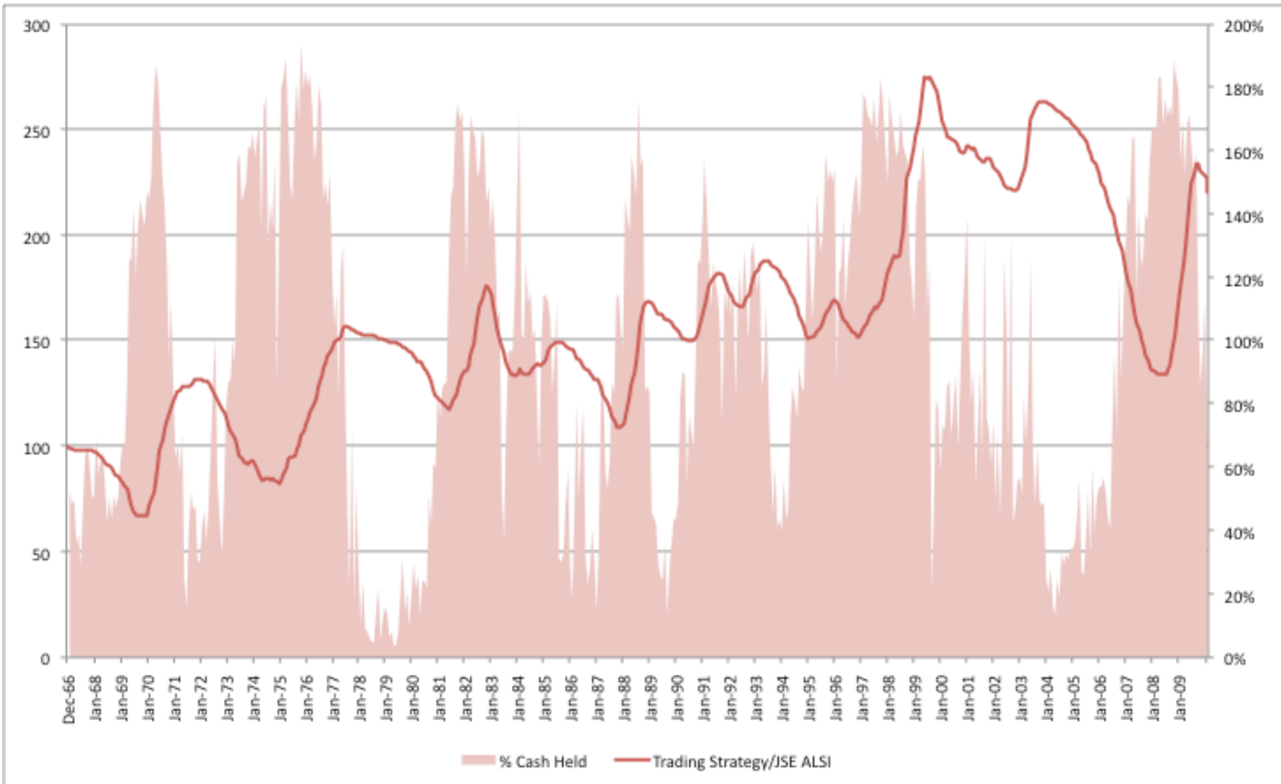
An analysis of indices provides a visual aid to determine periods of positive and negative returns, but to more accurately compare the characteristics of outperformance, the graphs below shows the value of the cumulative strategy values relative to the cumulative ALSI value.

Figure 7.17 Cumulative Outperformance of 1-Month Trading Strategy Performance relative to JSE ALSI



The figure above of 1-month trading strategy C's performance relative to the JSE ALSI highlights the underperformance over the sample period. However, this underperformance is not consistent throughout the time period. From 1967 to 1978, the value of the strategy and the JSE ALSI are roughly the same, although there are periods of relative over and under-performance within. However, there is a sharp decline after 1978 and, although it reversed temporarily during 1982 during the negative returns realised by the JSE ALSI, the value of strategy C returns to roughly 80% the value of the JSE ALSI. There is then a period of underperformance in the run-up to the crash in 1988 and a period of outperformance during the crash. However, the value of trading strategy C then declines to roughly 60% the value of the JSE ALSI and hovers around there until 2004. The strategy then underperforms in the build-up to the subprime crisis, before reversing some of that underperformance during the subprime related JSE ALSI crash. However, this period of outperformance is reversed shortly thereafter, as the market reverses a portion of its previous losses. Thus, although there are periods of sharp temporary outperformance, the strategy as a whole has a clear trend of underperformance from 1979 onwards.

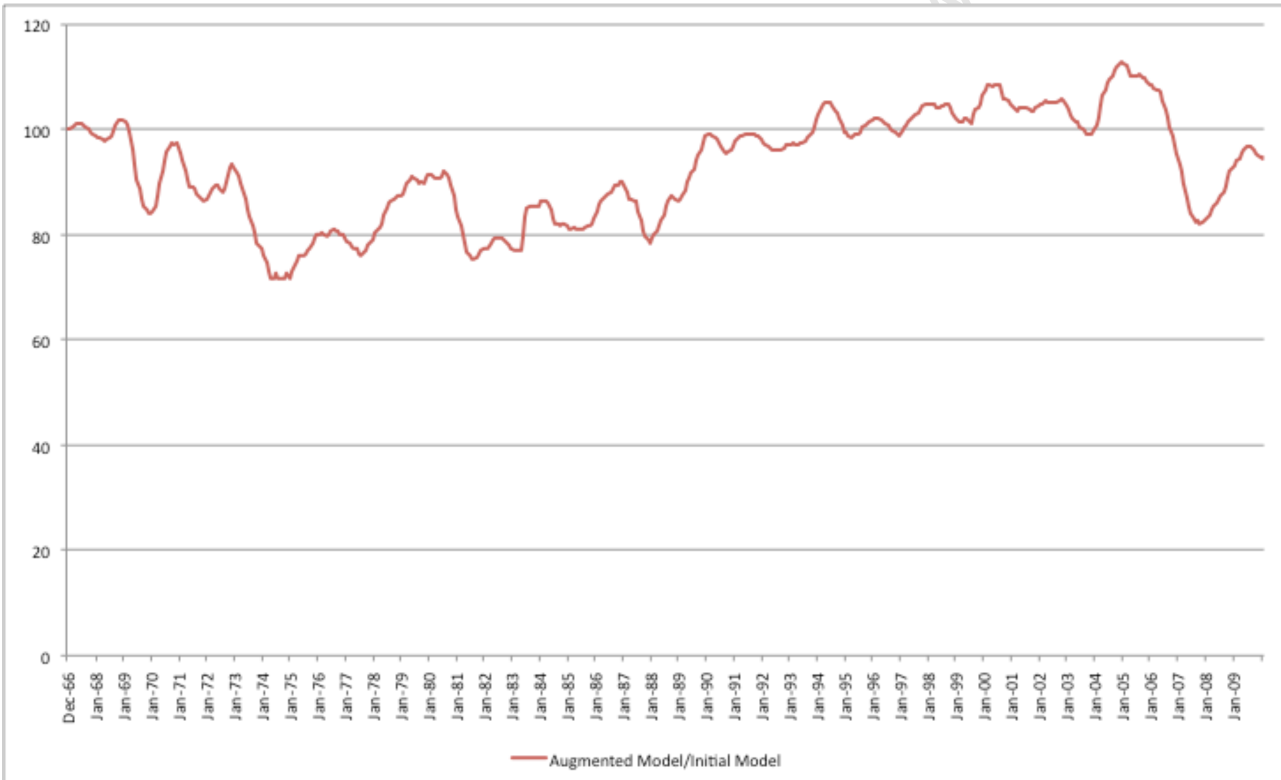
Figure 7.18 Cumulative Outperformance of 12-Month Trading Strategy C relative to JSE ALSI



Unlike the 1-month trading strategy, the 12-month trading strategy outperforms the JSE ALSI. However, the pattern of outperformance is not a consistent trend through time, with periods of several years where there is steep underperformance. This mostly occurs when a cash position in excess of 100% and a short position in the JSE ALSI is taken based on forecasts predicting a crash that only occurs several years later. Therefore, the strategy tends to underperform for several years as the position both earns a lower return on the risk-free asset and a negative return on its short position on the JSE ALSI, before the JSE ALSI drops dramatically, leading to a reversal of this underperformance as positive returns are made from the long position in the risk-free asset and from the short position in the negative yielding JSE ALSI. These periods of underperformance can be drastic, such as during the build-up to the subprime crisis, from 2004 onwards, when 50% of the cumulative relative outperformance is lost, before the losses are mostly reversed during the subprime related crash in 2008.

Finally, to compare the performance of the trading strategies based on the two forecast models, the relative value of the highest yielding return horizon of the augmented model based trading strategy C (12-months) against the highest yielding return horizon of the initial model based trading strategy C (24-months).

Figure 7.19 Cumulative Outperformance of 12-Month Augmented Forecast model Trading Strategy C Performance relative to 24-Month Inital Forecast model Trading Strategy C



The pattern of outperformance of the augmented model based strategy relative to the initial model based strategy suggests that there are periods of relative outperformance and underperformance. From 1967 to 1979, there is a trend of underperformance of the augmented model based strategy relative to the initial model based strategy. But from 1980 until 2006, the augmented model based strategy outperforms the initial model based strategy. But from 2006 to 2008, the augmented model based strategy sharply underperforms, and although the strategy recovers some of the cumulative underperformance from 2008 onwards, roughly 50% of the cumulative outperformance generated over the previous 26 years is still lost. This suggests that the augmented model's forecasts are generally superior, but time the subprime crisis several years too early. In a strategy that can be heavily invested in a short position, this incorrect timing yields strongly negative results.

Conclusions

Like the initial forecast model, the findings above show that it is possible to exploit a predictive timing model and generate returns in excess of those realised by the JSE ALSI. The second finding is that the strategy employed to use the forecasts generate a different return pattern. Like the initial forecast model, trading strategy A generates the highest absolute returns, but with the greatest levels of total risk, while trading strategy C leads to the lowest levels of total risk and the highest levels of risk-adjusted returns. The third conclusion is how the choice in portfolio holding periods leads to different results. A 1-month holding period consistently leads to the highest risk-adjusted returns, probably due to the lower variation in forecasts around 50%, but also to the lowest absolute returns. Longer return horizons, such as 6-month returns for Trading Strategies A and 12-month returns for Trading Strategies B and C, lead to the highest absolute returns, but with higher risk, as the forecasts have a greater spread between 0 and 100, allowing the strategies to more successfully to exploit correct timing of market conditions.

The augmented model also has superior performance to the initial model across respective return timeframes. The inclusion of additional information content of longer-term returns thereby increases the predictive capabilities of the model. Therefore, the augmented model should replace the initial model when developing a trading strategy.

However, both forecast models have a substantial look-ahead bias in that the estimates are provided at the end of the sample. Thus, these coefficients are estimated with data that is only available at a later period. In addition to this, the choice of variables is based on correlation analysis utilising the full sample. Thus, the model specification is also subject to significant look-ahead bias. To correct for these biases, the next chapter recreates the methodology that develops the augmented forecast model utilising only the data that is available at each point of time.

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8 Results: Dynamically Updating Out-of-Sample Models

The preceding chapters analyse the potential benefit in utilising a multifactor forecast model as part of a market timing strategy. The results indicate that models display predictive power and utilising these forecasts in various trading strategies, excess returns and risk-adjusted returns may be realised. However, the creation of the multifactor forecast model utilises all data available in the sample. There is therefore an inherent look-ahead bias present in the earlier results. This chapter adjusts the methodology to minimise any look-ahead biases. In 8.1, the methodology to overcome this bias is described. In 8.2, the new, dynamically updating ordinary least squares regression estimations are estimated and their predictive power analysed. In 8.3, the forecasts generated in 8.2 are applied to three trading strategies and the results analysed. In 8.4, the assumption of zero transaction costs is relaxed and the impact on excess returns is analysed.

8.1 Adjusted Methodology to Overcome Look-Ahead Biases

The inherent look-ahead bias in the prior chapters arises in two forms. The first is that the coefficients in the model are fitted to minimise the standard error of the prediction or, alternatively stated, to maximise the predictive power of the model. However, the models created in chapters 5 and 6 are determining estimates of the coefficients based on the entire sample of data, which is impossible in real-time, as the data of future movements in returns and the independent variables that relate to returns are unable until the end of the study. One would expect that the estimates of the coefficients, utilising a limited dataset up to that point, would generate inferior forecasts than estimates generated utilising the full dataset.

The second manifestation of the bias is in the selection of relevant dependent variables. According to the methodology formulated above, a variable is included if the probability of it being correlated with future returns is significant at the 10% level. By using the entire sample, the study is choosing variables that are significantly correlated with returns over the entire time period, which will increase the predictive power of the selection as

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only the variables that are proven to be the best over the entire sample will be chosen. However, these correlations change from period to period and it is unlikely that the variables selected will be the optimal variables throughout the time period.

To overcome this bias, a methodology similar to Pesaran and Timmermann (1995) is employed. The data is artificially limited at any given point in time and a model is determined with that data. The model then forecasts one period out-of-sample. These forecasts are then used in the previously used hypothetical trading strategies, to compare a more realistic investment process against the JSE ALSI.

However, there are several choices in model specification. The first is the choice between a rolling model and an expanding horizon model, with the choice also then dependent on the size of the roll and the minimum number of data points required respectively. To accommodate these variations, 5, 7 and 10-year rolling regressions are estimated, as well as a 10-year expanding window, where the initial sample is augmented with the inclusion of new observations as they become available. The second is the choice between the augmented model and the initial model. The results above indicate that the augmented model generates greater return performance – however that result is only known at the end of the sample. However, the additional computing complexity to dynamically choose between the two potential models is beyond the scope of the study. Additionally, the coefficient estimates of the implicit forecasts in the augmented model will only differ from zero if there is a historical relationship, after holding other variables constant. Therefore, it is likely that an investor would include these forecasts regardless of their prior performance.

Therefore, the dynamically updated model will take the form of the augmented model. A cointegrating relationship will be generated using an expanding horizon, with a minimum of 10 years (120 data points required). Once the cointegrating relationship is generated, the probabilities of a correlation between the residual and the other potential predictive variables with future returns are calculated, again using an expanding dataset with a minimum of 120 data points. The variables that are significant at the 10% level are then included in the model. However, this may create severe multicollinearity if certain variables are included that are the same basic measure of certain information (for example, 6 and 12-month earnings growth). To circumvent this problem, the variables are broken up into several groups, listed below.

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Table 8.1 Groups of Variables

Category	Relevant Variables		
Ungrouped	Earnings Yield	Dividend Yield	Cointegrating Residual
Adjusted Earnings Yield	RLRS Adjusted Earnings Yield	RBAS Adjusted Earnings Yield	
Adjusted Dividend Yield	RLRS Adjusted Dividend Yield	RBAS Adjusted Dividend Yield	
Earnings Growth	6-Month Earnings Growth	12-Month Earnings Growth	18-Month Earnings Growth
	24-Month Earnings Growth	36-Month Earnings Growth	48-Month Earnings Growth
Interest Rate Variables	RLRS	RBAS	Term Spread
Short-Term Overbought/Sold Indicator	90-Day Overbought/Sold	120-Day Overbought/Sold	150-Day Overbought/Sold
	180-Day Overbought/Sold		
Long-Term Overbought/Sold Indicator	1-Year Overbought/Sold	2-Year Overbought/Sold	3-Year Overbought/Sold
	5-Year Overbought/Sold	10-Year Overbought/Sold	
Short-Term Historic Returns	1-Month Historic Returns	3-Month Historic Returns	6-Month Historic Returns
Long-Term Historic Returns	12-Month Historic Returns	18-Month Historic Returns	24-Month Historic Returns
	36-Month Historic Returns	48-Month Historic Returns	60-Month Historic Returns
P/E Differences	Deviation from 3-Year P/E	Deviation from 5-Year P/E	Deviation from 10-Year P/E
	% Difference from 3-Year P/E	% Difference from 5-Year P/E	% Difference from 10-Year P/E

Earnings Yield is measured as EPS/P. Dividend Yield is measured as DPS/P. RLRS Adjusted Earnings Yield is measured as Earnings Yield/RLRS. RLRS Adjusted Dividend Yield is measured as Dividend Yield/RLRS. RBAS Adjusted Earnings Yield is measured as Earnings Yield/RBAS. RBAS Adjusted Dividend Yield is measured as Dividend Yield/RBAS. T-Month Earnings Growth is measured as ln(EPS(t))-ln(EPS(t-T)). Term Spread is calculated as RLRS – RBAS. % Overbought/Sold Indicator is measured as $(P_t\text{-}MA_t)/MA_t$. T-period historic returns are calculated as $\ln(ALSI_t)\text{-}\ln(ALSI_{t-T})$. Deviation from moving average is calculated as $(PE_t\text{-}MA_t)$. % difference from moving average is calculated as $(PE_t\text{-}MA_t)/(MA_t)$.

If there is more than one variable within a group that has a significant correlation with future returns, at the 10% level, only the variable that has the highest correlation is selected.

Once the variables are chosen and estimated, the implicit forecasts are then calculated as $\overline{Y}_{t,t+T} = E\left[Y_{t-Z,t+T} \mid X_{t-Z}\right] - R_{t-Z,t}$; $Z > T > 0$, where $\overline{Y}_{t,t+T}$ is the forecasted return on the market from period t to period t+T, $R_{t,t-Z}$ is the actual return realised from period t-Z to period t, T is the length of the short-

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term forecast, T+Z is the length of the long-term forecast, and X_i is a vector of variables, at time t-Z+T, used to generate the long-term forecast. The final augmented model is then estimated by including the variables included in the initial model with the implicit forecasts of the longer-term returns. Finally, an out-of-sample prediction is created. The models are then estimated using the differing rolling and expanding window variations described above.

As all the regressions require a minimum of 10 years of data to generate the cointegrating and initial regression models and that certain variables only have data starting in 1970, this becomes the starting point of the models. However, to fit a return model, the future return of t periods ahead (where t is the return horizon) is also required. The longest return horizon for the initial regression models is a 2-year return and, for the longest training periods, ten-years of history is required. This therefore creates a sample from the beginning of January 1982 to the end of February 2011 - a period of just over 29 years.

Due to the continuously changing specification of the final augmented model and the underlying augmented models, as well as the number of specifications, the coefficient estimates are not provided in the study (the code created for the dynamically updating out-of-sample model estimation will be provided on request). However, the performance of the forecasts yielded by these models is captured below in the form of a regression analysis of forecasts against actual and the rate of success (hit-rate) of the direction of the forecasts matching the actual direction of returns over the time horizon.

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8.2 Results of Dynamically Updating Out-of-Sample Models

The regression analysis of predicted versus actual returns should yield an intercept coefficient of zero, a slope coefficient of one and a R^2 of 100% if the forecast models generated perfect forecasts. Any deviation from this case indicates a forecast bias and an inefficiency of forecasts.

The OLS estimations of the dynamically updated out-of-sample forecasts against actual returns are presented below, along with the OLS estimation of the forecasts generated by the entire sample forecast models.

Table 8.2 OLS Estimation of Predicted versus Actual Returns – 1 Month Returns

	Intercept		Slope		R^2
10-Year Expanding	-0.0013	(0.25)	**0.0164**	(0.00)	0.00
5-Year Rolling	**0.0082**	(0.01)	**-0.0923**	(0.00)	0.01
7-Year Rolling	**0.0129**	(0.00)	**0.0425**	(0.00)	0.00
10-Year Rolling	**0.0087**	(0.00)	**0.0267**	(0.00)	0.00
Static – Entire Sample	**-0.0020**	(0.00)	**0.0392**	(0.00)	0.04

OLS Coefficients (p-value of differences from 0 for intercept and 1 for slope) and R^2. Bolded figures indicate significance at the 10% level.

Table 8.3 OLS Estimation of Predicted versus Actual Returns – 3 Month Returns

	Intercept		Slope		R^2
10-Year Expanding	**0.0125**	(0.00)	**0.0489**	(0.00)	0.01
5-Year Rolling	**0.0351**	(0.00)	**-0.1124**	(0.00)	0.01
7-Year Rolling	**0.0455**	(0.00)	**0.1244**	(0.00)	0.01
10-Year Rolling	**0.0376**	(0.00)	**0.0829**	(0.00)	0.00
Static – Entire Sample	**-0.0058**	(0.00)	**0.1208**	(0.00)	0.15

OLS Coefficients (p-value of differences from 0 for intercept and 1 for slope) and R^2. Bolded figures indicate significance at the 10% level.

Table 8.4 OLS Estimation of Predicted versus Actual Returns – 6 Month Returns

	Intercept		Slope		R^2
10-Year Expanding	**0.0204**	(0.00)	**0.0107**	(0.00)	0.00
5-Year Rolling	0.0048	(0.74)	**-0.3184**	(0.00)	0.05
7-Year Rolling	-0.0066	(0.57)	**-0.0746**	(0.00)	0.00
10-Year Rolling	0.0059	(0.53)	**-0.0112**	(0.00)	0.00
Static – Entire Sample	0.0024	(0.50)	**0.2108**	(0.00)	0.24

OLS Coefficients (p-value of differences from 0 for intercept and 1 for slope) and R^2. Bolded figures indicate significance at the 10% level.

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Table 8.5 OLS Estimation of Predicted versus Actual Returns – 12 Month Returns

	Intercept		Slope		R^2
10-Year Expanding	**0.0354**	(0.00)	**0.0235**	(0.00)	0.00
5-Year Rolling	-0.0098	(0.65)	**-0.0483**	(0.00)	0.00
7-Year Rolling	-0.0125	(0.45)	**-0.0789**	(0.00)	0.00
10-Year Rolling	-0.0080	(0.61)	**0.0274**	(0.00)	0.00
Static – Entire Sample	-0.0003	(0.96)	**0.3542**	(0.00)	0.35

OLS Coefficients (p-value of differences from 0 for intercept and 1 for slope) and R^2. Bolded figures indicate significance at the 10% level.

The most notable finding is the extremely low R^2 of the predicted versus actual returns. This indicates that, once accounting for a look-ahead bias in determining both the estimation and choice of coefficients, the predictive power of the models is near zero.

A second finding is that, across return methodologies and return horizons, the slope coefficients are statistically significantly less, at the 10% level, than one. If the slope coefficient lies between zero and one, this indicates that the absolute magnitude of predicted returns is consistently less than actual returns. This implies that the forecasts continuously understate the size of returns. However, the slope coefficient of the forecasts against actual returns is negative for all return horizon forecasts generated from the 5-year rolling regression specification, for 6 and 12-month return horizon forecasts generated from the 7-year rolling regression specification, and for 6-month return horizon forecasts generated from the 10-year rolling regression. These negative coefficients imply that the forecasts, apart from being inaccurate, systematically predict the direction of returns incorrectly.

Thirdly, there is a statistically significant, at the 10% level, forecast bias for all specification of models for 1 and 3-month returns, with the exception of the expanding window specification for 1-month returns. For 1-month returns, this forecast bias ranges from 0.13% to 1.3%, in absolute terms and for 3-month returns, it ranges from 0.6% to 4.6%, in absolute terms. The static entire sample and expanding window model specifications also have the smallest biases, while the rolling window, and the 7-year rolling window in particular, have the largest biases. However, for 6 and 12-month returns, only the forecasts generated by the expanding window forecast have a

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statistically significant, at the 10% level, forecast bias, of 2% and 3.5% respectively. In the larger sample analysis above, there are significant biases, irrespective of return horizons. However, in replicating this methodology over the shorter sample, this forecast bias is no longer statistically significant over this time period. This indicates that this finding is due to the period chosen and not through the use of a superior methodology.

The extremely low R^2 of the dynamically updating out-of-sample models indicates that the attempt to forecast returns using models that are free of look-ahead bias leads to highly inaccurate forecasts. The incorrect sign on the slope coefficient of this regression analysis for longer-term returns using a rolling-window methodology indicates that this methodology leads to systematically incorrect forecasts over 6 and 12-month returns. In summary, these findings suggest that it is unlikely to specify and successfully exploit a market-timing model created using this methodology.

However, even the models generated without correcting for a look-ahead bias did not provide highly accurate forecasts that did not have certain systematic biases. A model may also be unable to accurately predict the exact magnitude of returns but have a greater success at predicting the direction of returns, which can be utilised to generate excess returns. To gauge the dynamically updating out-of-sample models ability to predict return direction, a hit-rate is constructed (as above), with both the hit-rates of the static, entire sample model and a model that always forecasts a positive excess return by the JSE ALSI over a risk-free rate provided for comparison.

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Table 8.6 Hit-Rates

	1-Month	3-Month	6-Month	12-Month
10-Year Expanding	50.15%	55.52%	**62.35%**	**64.72%**
5-Year Rolling	47.77%	53.73%	44.58%	50.31%
7-Year Rolling	52.52%	**62.99%**	47.89%	50.92%
10-Year Rolling	53.71%	**62.09%**	56.33%	**57.67%**
Static – Entire Sample	**56.08%**	**63.28%**	**70.18%**	**74.54%**
Benchmark	54.30%	56.72%	59.04%	52.76%

Bolded figures indicate a hit-rate above the benchmark.

Of the dynamically updating out-of-sample models, the 5-year rolling model has the lowest hit-rate across return horizons, indicating it has the lowest ability in predicting return direction. Of the other dynamically updating out-of-sample models, the 10-year rolling window specification has the highest hit-rate over a 1-month return horizon, the 7-year rolling window specification has the highest hit-rate over a 3-month return horizon, and the 10-year expanding window specification has the highest hit-rate over 6 and 12-month return horizons. The return direction performance of the expanding window horizon over longer return horizons is unsurprising, considering the results of the regression analysis above. All hit-rates are lower than the hit-rates generated by the static, entire sample model, which is also unsurprising, as these static models have substantial look-ahead biases. However, for 3-month returns, the difference between the hit-rates of the forecasts generated by this model relative to the forecasts generated by the 7-year rolling window model is less than 0.3%.

However, the hit-rates are not consistently higher than the benchmark across all return horizons, with different specifications exceeding the benchmark hit-rate in different return horizons. The hit-rate for forecasts generated by the 5-year rolling window model for 1 and 6-month returns and by the 7-year rolling window model for 6-month returns is less than 50%, implying that a completely random choice between positive and negative excess returns will more successfully predict the direction of returns than by using the forecasts generated by these models.

In summary, an analysis of the hit-rates indicates that the models may be able to predict the direction of returns in a manner that can generate excess returns. However, this is dependent on the choice of model over the return horizon, with an incorrect choice leading to forecasts that are worse than a purely random guess.

8.3 Performance of Forecasts Applied to Trading Strategies

To determine whether a model generates forecasts that can generate excess returns, these forecasts need to be incorporated into a trading strategy. The trading strategies that are used to test this are the same as above. To summarise, it is a two-asset portfolio of the JSE ALSI and a risk-free asset, using the 90-Day Bankers Discount Rate as a proxy. The rules of each trading strategy are tabulated below.

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Table 8.7 Trading Strategy Rules

	Trading Strategy A	Trading Strategy B	Trading Strategy C
JSE ALSI	100% if p > 50%; 0% if p <= 50%	p%	(2p – 100)%
RBAS	0% if p > 50%; 100% if p <= 50%	(100-p)%	(200 – 2p)%

P is the probability that the JSE ALSI will yield a positive return over the relevant holding period.

To implement strategies longer than one-month, it is assumed that the investor breaks up their investment into x equal portions, where x is the length of the return horizon, and invests each portion for the full length of the forecasts return horizon at time t.

The metrics of performance are annualised absolute returns, annualised standard deviations, risk-adjusted returns and annualised Jensen's alphas, calculated as specified in the previous chapter. The performance metrics of these trading strategies for all dynamically updated out-of-sample model specifications and the static, entire sample, as well as the performance of a pure buy-and-hold strategy in the JSE ALSI are reported below.

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Table 8.8 Trading Strategy A Results from Different Specifications

		10-Year Expanding	5-Year Rolling	7-Year Rolling	10-Year Rolling	Static	JSE ALSI
1-Month	Average Annualised Return	17.20%	15.75%	**21.18%**	**19.37%**	**23.59%**	18.23%
	Annualised Standard Deviation	**13.56%**	**15.76%**	**14.01%**	**14.13%**	**13.51%**	21.54%
	Risk-Adjusted Return	**1.27**	**1.00**	**1.51**	**1.37**	**1.75**	0.85
	Average % Cash	50.15%	47.18%	44.21%	42.43%	55.79%	0%
	Annualised Jensen's Alpha	**2.09%**	**0.14%**	**5.40%**	**3.81%**	**7.67%**	0%
3-Month	Average Annualised Return	16.15%	15.89%	**20.52%**	**19.17%**	**25.25%**	18.53%
	Annualised Standard Deviation	**17.83%**	**16.01%**	**18.30%**	**17.52%**	**15.56%**	23.12%
	Risk-Adjusted Return	**0.91**	**0.99**	**1.12**	**1.09**	**1.62**	0.80
	Average % Cash	33.73%	46.27%	36.42%	34.33%	53.73%	0%
	Annualised Jensen's Alpha	**0.10%**	**0.46%**	**3.73%**	**2.84%**	**8.71%**	0%
6-Month	Average Annualised Return	17.52%	13.81%	14.21%	16.17%	**24.84%**	18.89%
	Annualised Standard Deviation	**17.79%**	**15.50%**	**16.81%**	**17.21%**	**17.70%**	24.26%
	Risk-Adjusted Return	**0.99**	**0.89**	**0.85**	**0.94**	**1.40**	0.78
	Average % Cash	32.23%	54.22%	49.10%	39.46%	43.07%	0%
	Annualised Jensen's Alpha	**1.51%**	-1.12%	-1.14%	**0.45%**	**7.76%**	0%

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Table 8.8 Trading Strategy A Results from Different Specifications

12-Month	Average Annualised Return	16.98%	15.17%	14.66%	16.06%	**22.19%**	18.34%
	Annualised Standard Deviation	**19.81%**	**16.93%**	**17.45%**	**19.43%**	**18.66%**	24.55%
	Risk-Adjusted Return	**0.86**	**0.90**	**0.84**	**0.83**	**1.19**	0.75
	Average % Cash	26.69%	52.15%	49.08%	35.58%	49.39%	0%
	Annualised Jensen's Alpha	**0.59%**	**0.27%**	-0.37%	-0.02%	**5.79%**	0%

Sample Period: January 1982 – January 2010. Average Annualised Returns are calculated as average t-period returns over the sample period multiplied by 12/t. The Annualised Standard Deviations are calculated as the standard deviation of returns over the sample period multiplied by the square root of 12/t. Risk-Adjusted Returns are calculated as average annualised return/annualised standard deviation. Annualised Jensen's alpha is calculated as the annualised C in the regression equation: Excess Returns(Trading Strategy) = C + Beta(Excess Returns(JSE ALSI)). Bolded figures outperform the JSE ALSI.

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Table 8.9 Trading Strategy B Results from Different Specifications

		10-Year Expanding	5-Year Rolling	7-Year Rolling	10-Year Rolling	Static Entire Sample	JSE ALSI
1-Month	Average Annualised Return	16.55%	15.05%	18.00%	17.38%	17.34%	18.23%
	Annualised Standard Deviation	**10.33%**	**13.08%**	**12.18%**	**11.60%**	**10.31%**	21.54%
	Risk-Adjusted Return	**1.60**	**1.15**	**1.48**	**1.50**	**1.68**	0.85
	Average % Cash	50.63%	46.10%	43.91%	44.86%	51.19%	0%
	Annualised Jensen's Alpha	**0.60%**	-0.91%	**1.64%**	**1.22%**	**1.22%**	0%
3-Month	Average Annualised Return	17.27%	15.40%	**19.38%**	18.10%	**18.70%**	18.53%
	Annualised Standard Deviation	**12.17%**	**14.82%**	**15.07%**	**14.34%**	**11.29%**	23.12%
	Risk-Adjusted Return	**1.42**	**1.04**	**1.29**	**1.26**	**1.66**	0.80
	Average % Cash	45.87%	46.55%	40.54%	41.25%	51.81%	0%
	Annualised Jensen's Alpha	**0.92%**	-0.42%	**2.60%**	**1.65%**	**2.27%**	0%
6-Month	Average Annualised Return	16.84%	13.56%	14.85%	15.96%	**19.74%**	18.89%
	Annualised Standard Deviation	**11.83%**	**12.96%**	**13.12%**	**12.65%**	**12.78%**	24.26%
	Risk-Adjusted Return	**1.42**	**1.05**	**1.13**	**1.26**	**1.54**	0.78
	Average % Cash	45.72%	55.62%	52.38%	48.94%	48.81%	0%
	Annualised Jensen's Alpha	**0.61%**	-1.69%	-0.93%	**0.14%**	**2.99%**	0%

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Table 8.9 Trading Strategy B Results from Different Specifications

12-Month	Average Annualised Return	16.46%	15.39%	14.61%	15.75%	**19.57%**	18.34%
	Annualised Standard Deviation	**12.63%**	**14.03%**	**13.94%**	**14.40%**	**14.51%**	24.55%
	Risk-Adjusted Return	**1.30**	**1.10**	**1.05**	**1.09**	**1.35**	0.75
	Average % Cash	44.07%	52.86%	52.26%	47.21%	49.26%	0%
	Annualised Jensen's Alpha	**0.31%**	-0.13%	-0.78%	-0.17%	**3.18%**	0%

Sample Period: January 1982 – January 2010. Average Annualised Returns are calculated as average t-period returns over the sample period multiplied by 12/t. The Annualised Standard Deviations are calculated as the standard deviation of returns over the sample period multiplied by the square root of 12/t. Risk-Adjusted Returns are calculated as average annualised return/annualised standard deviation. Annualised Jensen's alpha is calculated as the annualised C in the regression equation: Excess Returns(Trading Strategy) = C + Beta(Excess Returns(JSE ALSI)). Bolded figures outperform the JSE ALSI.

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Table 8.10 Trading Strategy C Results from Different Specifications

		10-Year Expanding	5-Year Rolling	7-Year Rolling	10-Year Rolling	Static Entire Sample	JSE ALSI
1-Month	Average Annualised Return	13.28%	10.42%	16.22%	14.91%	14.91%	18.23%
	Annualised Standard Deviation	**5.55%**	**12.28%**	**9.47%**	**9.02%**	**3.44%**	21.54%
	Risk-Adjusted Return	**2.39**	**0.85**	**1.71**	**1.65**	**4.34**	0.85
	Average % Cash	101.25%	92.21%	87.81%	89.72%	102.38%	0%
	Annualised Jensen's Alpha	**1.21%**	-1.81%	**3.30%**	**2.46%**	**2.46%**	0%
3-Month	Average Annualised Return	14.36%	10.02%	18.48%	15.84%	17.10%	18.53%
	Annualised Standard Deviation	**8.13%**	**18.40%**	**15.11%**	**14.65%**	**5.59%**	23.12%
	Risk-Adjusted Return	**1.77**	0.54	**1.22**	**1.08**	**3.06**	0.80
	Average % Cash	91.75%	93.10%	81.08%	82.49%	103.63%	0%
	Annualised Jensen's Alpha	**1.85%**	-0.84%	**5.26%**	**3.33%**	**4.57%**	0%
6-Month	Average Annualised Return	12.60%	5.11%	8.06%	10.36%	18.79%	18.89%
	Annualised Standard Deviation	**9.30%**	**18.65%**	**16.02%**	**15.28%**	**8.47%**	24.26%
	Risk-Adjusted Return	**1.35**	0.27	0.50	0.68	**2.22**	0.78
	Average % Cash	91.45%	111.25%	104.76%	97.88%	97.62%	0%
	Annualised Jensen's Alpha	**1.22%**	-3.37%	-1.85%	**0.28%**	**6.03%**	0%

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Table 8.10 Trading Strategy C Results from Different Specifications

12-Month	Average Annualised Return	13.09%	10.19%	8.30%	11.23%	**19.34%**	18.34%
	Annualised Standard Deviation	**8.13%**	**17.76%**	**18.64%**	**15.93%**	**11.73%**	24.55%
	Risk-Adjusted Return	**1.61**	0.57	0.44	0.70	**1.65**	0.75
	Average % Cash	88.15%	105.72%	104.51%	94.42%	98.52%	0%
	Annualised Jensen's Alpha	**0.63%**	-0.27%	-1.57%	-0.34%	**6.36%**	0%

Sample Period: January 1982 – January 2010. Average Annualised Returns are calculated as average t-period returns over the sample period multiplied by 12/t. The Annualised Standard Deviations are calculated as the standard deviation of returns over the sample period multiplied by the square root of 12/t. Risk-Adjusted Returns are calculated as average annualised return/annualised standard deviation. Annualised Jensen's alpha is calculated as the annualised C in the regression equation: Excess Returns(Trading Strategy) = C + Beta(Excess Returns(JSE ALSI)). Bolded figures outperform the JSE ALSI.

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Irrespective of return horizon or model specification, trading strategy A generates lower standard deviations and higher risk-adjusted returns compared to a pure buy-and-hold strategy. The expanding window specification also generates positive Jensen's alpha across all return horizons, as does a 5-year rolling window for a 12-month return horizon and a 10-year rolling window for a 6-month return horizon. Only the 7 and 10-year rolling window specifications generate absolute returns in excess of the JSE ALSI, and it is only when used for a 1 or 3-month return horizon. With the exception of 1-month returns, the 10-year expanding window is in the risk-free position the fewest number of periods, with this increasing as the length of the rolling window decreases. There is also a trend to hold the JSE ALSI more often when the return horizon increases for the expanding window specification, but the rolling specifications are generally in the risk-free position less frequently for 1 and 3-month return horizons compared to the equivalent 6 and 12-month return horizon.

Of the specifications, the 7-year rolling window with a 1-month return horizon generates the highest absolute returns (21.18%), the highest risk-adjusted return (1.51) and the highest Jensen's alpha (5.4%), while the 10-year expanding window with a 1-month return horizon generates the lowest standard deviation (13.56%).

The choice in model specification also has an effect on the variations in performance over return horizons. The variations in returns across return horizons for strategies based on the 10-year expanding window and 5-year rolling window tend to be relatively stable, with the 10-year expanding window consistently outperforming the 5-year rolling window, compared to the 7 and 10-year rolling window strategies, which have substantially better performance over 1 and 3-month return horizons compared to their performance over 6 and 12-month return horizons.

The evidence above indicates that strategies based on forecast models may be used to generate excess returns. However, the characteristic of outperformance is important to analyse, as a strategy that outperforms over an entire period due to a one-off event is not a strategy that can be trusted to continuously outperform the benchmark. To analyse this, the cumulative performance of the strategy applied on a 1-month return horizon using the forecasts from a 7-year rolling window forecast model, chosen as it has the best absolute and risk-adjusted returns, is graphed against the cumulative performance of the ALSI, based to 100 and using a logarithmic axis scale.

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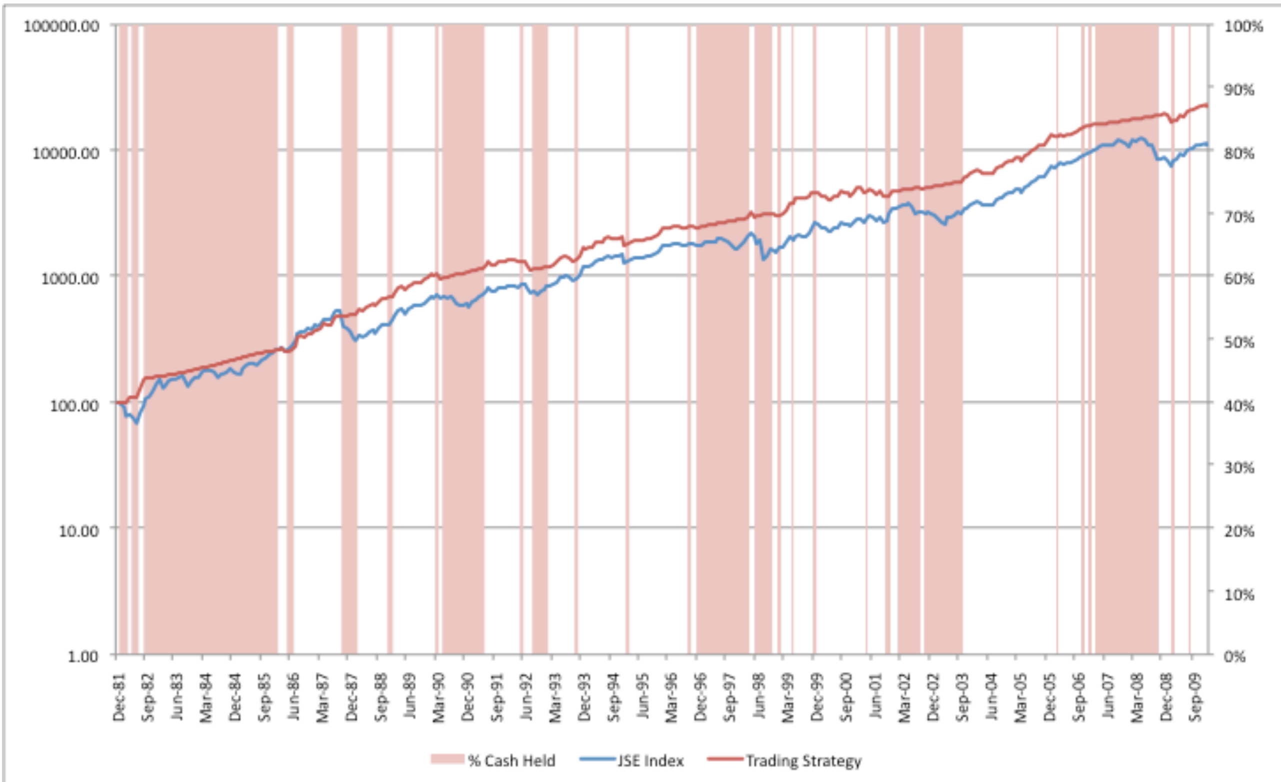
Figure 8.1 Cumulative Value of 7-Year Rolling Window Model 1-Month Trading Strategy A relative to the JSE ALSI



The graphic above indicates that the trading strategy generates its excess returns by being in the risk-free asset during periods when the market declines sharply. However, it often exits its position in the JSE ALSI several years before the downturn occurs and, on certain occasions, enters a cash position when no downturn ever emerges.

The strategy initially performs well by holding a cash position during the end of the downturn at the beginning of the 1980s. It switches to a position in the JSE ALSI during a sharp upward period, and then holds a cash position from the end of 1982 until the beginning of 1986. During this time period, the market is fairly stable, with returns exceeding those of the risk-free asset. The JSE ALSI therefore returns to a level similar to that of the trading strategy at the end of this period. For the next several years, the strategy mostly maintains a position in the JSE ALSI. However, the strategy switches out of the JSE ALSI shortly before Black Monday, thereby retaining the value it has accumulated over the past years. It then returns to a position in the JSE ALSI, with the

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exception of a few months, until mid-1990, when it switches to a cash position and holds this position until mid-1991. During this period, the JSE experiences a mild downturn followed by a reversal. From that point until the end of 1996, the strategy mostly holds a position in the JSE ALSI, but it then holds a cash position for most of the period from 1997 until the end of 1998. Due to this position, the strategy avoids the negative losses incurred by the market due to the Russian and Asian financial crises. The next major period when the strategy holds the risk-free asset is between the end of 2001 and the end of 2003, where it successfully avoids the negative returns caused by the reversal after a long period of positive returns caused by buoyant commodity prices. It then keeps a position in the JSE ALSI for most of the following 4 years, before switching to the risk-free asset in mid-2007. It holds this position until the end of 2008, forfeiting the strong positive returns at the top of the subprime bubble, but avoiding most of the negative returns that occurred due to the following recession and credit crunch.

As such, the trading strategy successfully avoided most of the major downturns in the JSE ALSI over the time period. However, it has often achieved lower returns, relative to a pure buy-and-hold strategy, for several years before this downturn. By holding the risk-free asset, which by nature has lower volatility than the JSE ALSI, and avoiding sharp downturns, the trading strategy is able to outperform a pure buy-and-hold trading strategy, in terms of absolute and risk-adjusted performance, over the sample period, with this outperformance occurring due to several events. To more accurately gauge periods of out and underperformance, the graph below shows the value of the cumulative strategy value relative to the cumulative ALSI value.

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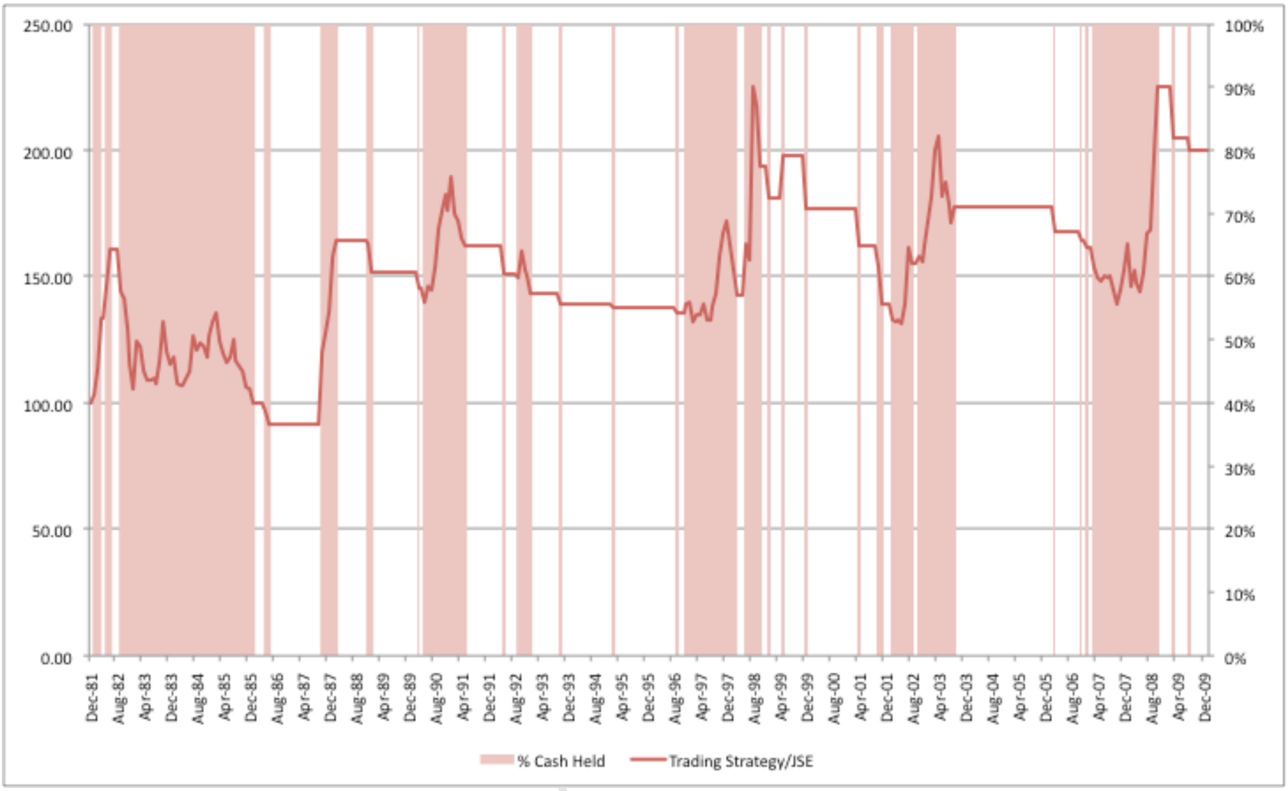
Figure 8.2 Cumulative Outperformance of 7-Year Rolling Window Model 1-Month Trading Strategy A relative to JSE ALSI



The graphic above reinforces most of the findings from the previous graph. The periods of greatest outperformance occurs during periods of sharp market declines, with several periods of underperformance occurring before. However, it also indicates that the switch in the trading strategy from the JSE ALSI to the risk-free asset for a few months between 1998 and 2002 led to sharp underperformance. These 'false signals' over this period therefore led to a substantial loss of value of the trading strategy, relative to the JSE ALSI, and eliminating these incorrect signals could lead to a substantially stronger strategy.

Trading Strategy B

Like trading strategy A, trading strategy B generates higher risk-adjusted returns and lower standard deviations of returns compared to a pure buy-and-hold strategy in the JSE ALSI. The strategy based on the 10-year expanding window also generates a positive Jensen's alpha across all return horizons, with the 7-year rolling specification generating a positive Jensen's alpha for 1 and 3-month return horizons and the 10-year rolling specification generating a positive Jensen's alpha for 1, 3 and 6-month return horizons. On an absolute return basis, only the 7-year rolling window specification applied to a 3-month return horizon generates returns in excess of the benchmark buy-and-hold strategy. The strategy based on the 5-year rolling specification generates the worst performance across metrics and the 10-year expanding window consistently generates the lowest standard deviations and the highest risk-adjusted returns of the dynamically updating out-of-sample models, holding return horizons constant. There is also a trend to be in the JSE ALSI more often when the return horizon increases for the expanding window specification, but the rolling specifications are generally in the risk-free position less frequently for 1 and 3-month return horizons compared to the equivalent 6 and 12-month return horizon.

The highest absolute returns (19.38%) and Jensen's alpha (2.60%) are generated from the trading strategy based on the 7-year rolling window model with a 3-month return horizon, and the highest risk-adjusted returns (1.60) and the lowest standard deviations (10.33%) are generated from the trading strategy based on the 10-year expanding window model with a 1-month return horizon.

Like trading strategy A, the choice in model specification has an effect on the performance metrics through return horizons. The strategy based on the expanding window has metrics that remain fairly constant irrespective of return horizon, while the strategies based on the rolling windows have metrics that are significantly higher for 1 and 3-month return horizons relative to 6 and 12-month return horizons.

To analyse the characteristics and persistence of performance, the cumulative value of the 7-year rolling window applied to 3-month return horizons, chosen as it has the highest absolute performance, and the 10-year expanding window applied to 1-month return horizons, chosen as it has the highest risk-adjusted performance, are graphed relative to the performance of a pure buy-and-hold strategy in the JSE ALSI.

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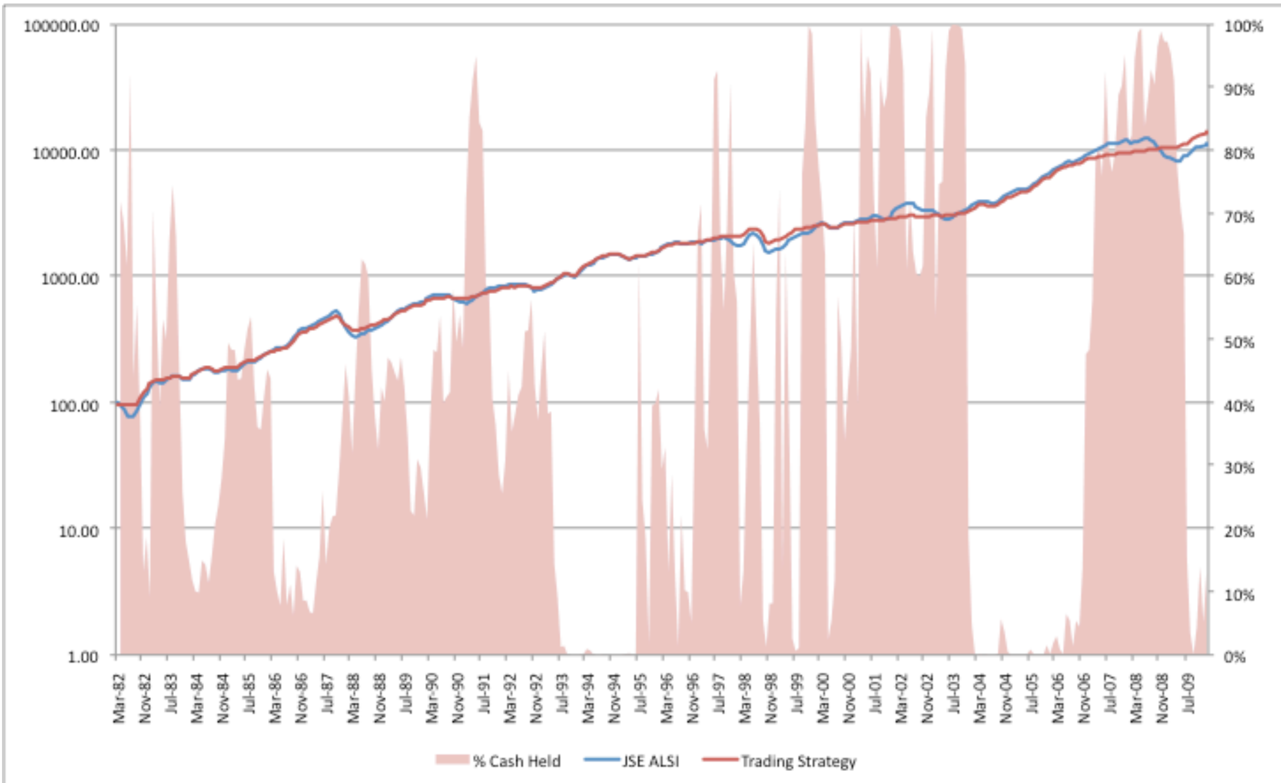
Figure 8.3 Cumulative Value of 7-Year Rolling Window Model 3-Month Trading Strategy B relative to the JSE ALSI



In the initial period of 1982, the strategy has a strong weighting in the risk-free asset, leading to flat returns over a period where the market declined sharply. The strategy then switches to a heavy weighting in the JSE ALSI in the succeeding run-up, before moving into a more balanced position. From 1983 until the end of 1990, the strategy is generally more heavily invested in the JSE ALSI, although it moves into a more equally weighted position from 1987 onwards. This ensures that it maintains the same positive trend as the JSE ALSI while not being heavily affected by any downturns in market conditions. In 1991, there is a strong shift to the risk-free asset, although the market remains fairly flat while this position is held. Therefore, the strategy doesn't strongly out or underperform, relative to the market. From 1992 until 1996, the strategy is generally invested in the risk-free asset, although there are several periods where it holds a more balanced position. However, these movements to a balanced position do not coincide with major movements in the JSE ALSI, leading to the strategy to retaining a similar value to the JSE ALSI. From 1996 to the end of 2000, the strategy is generally either heavily invested in the risk-free asset or the JSE ALSI. These switches in positions appear to accurately time the market from 1996-1998, leading to the strategy to outperform when the effects of the Russian and Asian financial crises effect South Africa. However, the heavy weighting in the risk-free asset in 1999 ensures that the strategy does not generate the strong returns of the JSE ALSI, leading to a loss in the earlier value created. From 2000 until the end of 2003, the strategy is strongly invested in the risk-free asset. Initially, this leads to a smaller increase in value compared to the JSE ALSI. However, when there is a market downturn after the long positive run caused by a commodity boom, the strategy retains its value, whereas the JSE ALSI loses its value. From 2004 until midway through 2007, the strategy is heavily invested in the JSE ALSI, participating in the strong bull cycle. After this period, the strategy then switches to a risk-free asset heavy position, thereby not participating in the returns at the peak of the bull cycle, but retaining value during the subprime crisis when the JSE ALSI loses value. From midway through 2009 onwards, the strategy moved to a heavy position in the JSE ALSI and participates in the returns that occur as the market corrects.

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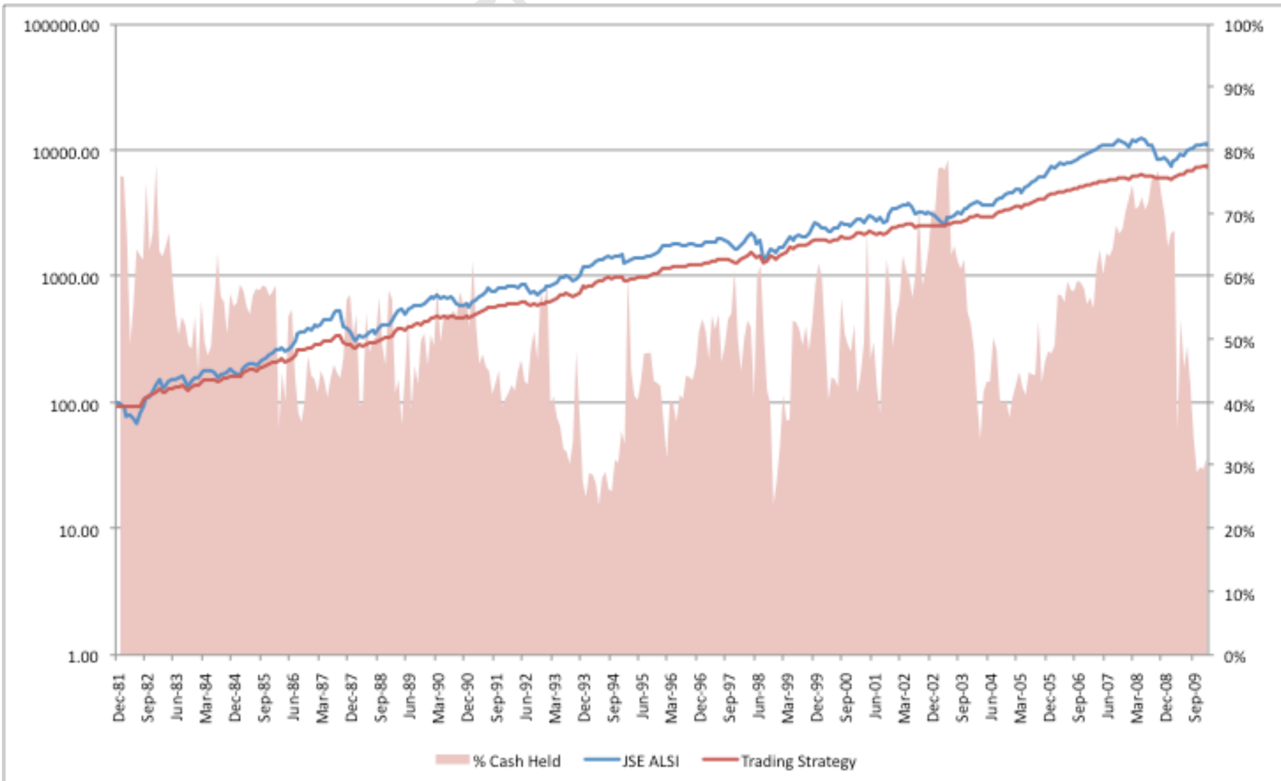
Figure 8.4 Cumulative Value of 10-Year Expanding Window Model 1-Month Trading Strategy B relative to the JSE ALSI



Unlike the variation of the strategy above, this strategy always remains fairly balanced between the risk-free asset and the JSE ALSI, with the maximum percentage weighting in one asset class less than 80%. Therefore, the pattern of returns is smoother through time compared to the JSE ALSI. However, as the JSE ALSI traditionally has a higher rate of return than a risk-free asset, the strategy cannot maintain the return performance of the JSE ALSI. During periods when the JSE ALSI strongly performs, the strategy loses value relative to the market portfolio, but when the JSE ALSI loses value, the strategy does not outperform significantly enough to reverse the previous losses. So, although there is evidence that the model is able to predict certain market downturns (notably the Asian and Russian financial crises and the subprime crisis), by construction, it is unable to move into a large enough weighting of the risk-free asset to reverse the previous years underperformance. That underperformance is also more significant because the strategy does not move into a large weighting of the JSE ALSI during bull periods.

To more clearly illustrate the pattern of out and underperformance, the graphs below shows the value of the cumulative strategy values relative to the cumulative ALSI value.

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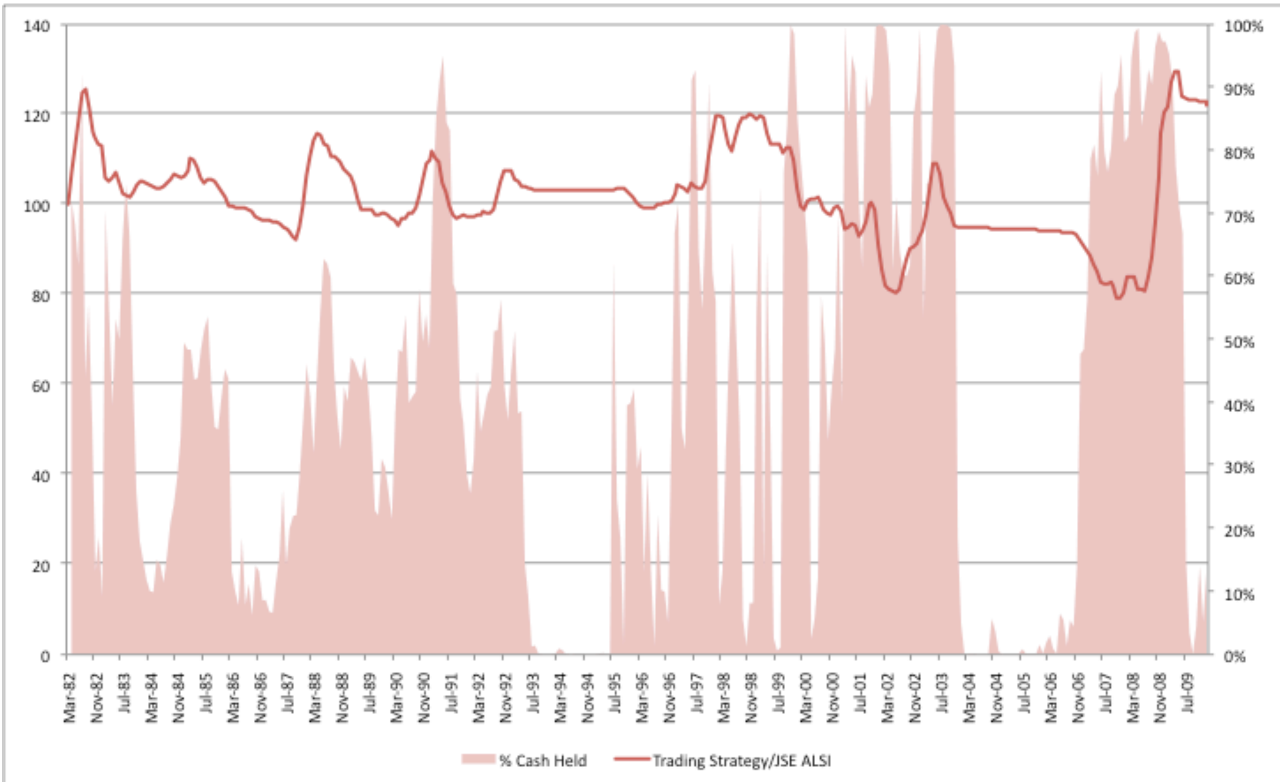
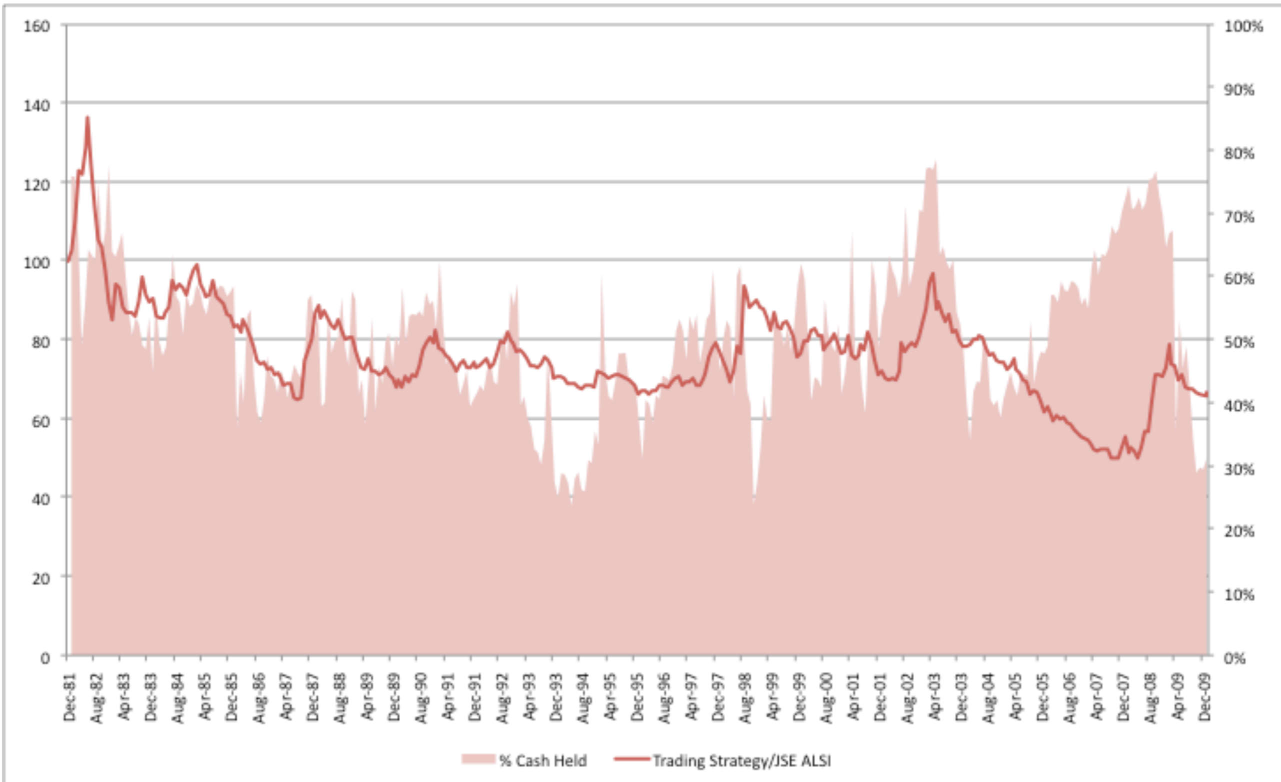
Figure 8.5 Cumulative Outperformance of 7-Year Rolling Window Model 3-Month Trading Strategy B relative to JSE ALSI



The graph of relative performance reinforces the pattern of outperformance seen by the strategies. During market declines, the strategy moves into a heavily weighted risk-free position and thereby outperforms compares to a market that loses value. However, during periods of strong market performance, the strategy tends to be partially invested in the risk-free asset and therefore underperforms relative to the JSE ALSI in this time period. However this weighting in the risk-free asset can also provide protection, as can be seen in 1987 to 1988, when the strategy outperforms compared to the JSE ALSI, but has not taken a strong position in either asset class. It is also clear that the model gives incorrect signals in 2000 to 2002, leading to strong underperformance, as the strategy does not participate in the strong JSE ALSI returns at the time.

Figure 8.6 Cumulative Outperformance of 10-Year Expanding Window Model 1-Month Trading Strategy B relative to the JSE ALSI



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The pattern of underperformance in this trading strategy more clearly shows the years of underperformance followed by a reversal when the JSE ALSI declines. However, during most cycles of the JSE ALSI, the strategy returns to the same value as the JSE ALSI (1985-1988, 1988-1999, 1999-2002). It is in the bull period from 2003 to mid-2008 that the strategy strongly underperforms. This underperformance is not caused by the construction of the strategy but by incorrect signals from the model, leading to the strategy to be more heavily invested in the risk-free asset than the JSE ALSI during a period of strong performance. Thus, even when the market crashes in late-2008, the strategy is unable to recuperate the loss in relative value over the previous few years.

Trading Strategy C

Trading strategy C leads to lower standard deviations of returns compared to the JSE ALSI across specifications and across return horizons. However, this reduction in risk does not necessarily lead to higher risk-adjusted returns. Only for a 1-month return horizon do all specifications generate higher risk-adjusted returns relative to the JSE ALSI, with all specifications except the 5-year rolling window specification generating higher risk-adjusted returns over a 3-month return horizon. For longer return horizons, only the 10-year expanding window specification generates risk-adjusted returns in excess of the JSE ALSI. The 10-year expanding window specification also generates positive Jensen's alpha across all return horizons, with the 7-year rolling window specification generating positive Jensen's alpha over 1 and 3-month return horizons and the 10-year rolling window specification generating positive Jensen's alpha over 1, 3 and 6-month return horizon. Irrespective of specification and return horizon, no portfolio generates absolute returns in excess of the JSE ALSI.

Like trading strategy B, the highest absolute returns (18.48%) and Jensen's alpha (5.26%) are generated from the trading strategy based on the 7-year rolling window model with a 3-month return horizon, and the highest risk-adjusted returns (2.39) and the lowest standard deviations (5.55%) are generated from the trading strategy based on the 10-year expanding window model with a 1-month return horizon.

It is also clear that, in absolute terms, different specifications have better performance in different return horizons. The longer rolling windows generate the highest returns for a 1 and 3-month return horizon, while the expanding window generates the highest returns for a 6 and 12-month return horizon. During the shorter return horizon, the strategies based on the rolling models tend to hold less average cash than the expanding window based strategy, with this reversing for 6 and 12-month return horizons.

To analyse the characteristics and persistence of performance, the cumulative value of the 7-year rolling window applied to 3-month return horizons, chosen as it has the highest absolute performance, and the 10-year expanding window applied to 1-month return horizons, chosen as it has the highest risk-adjusted performance, is graphed relative to the performance of a pure buy-and-hold strategy in the JSE ALSI.

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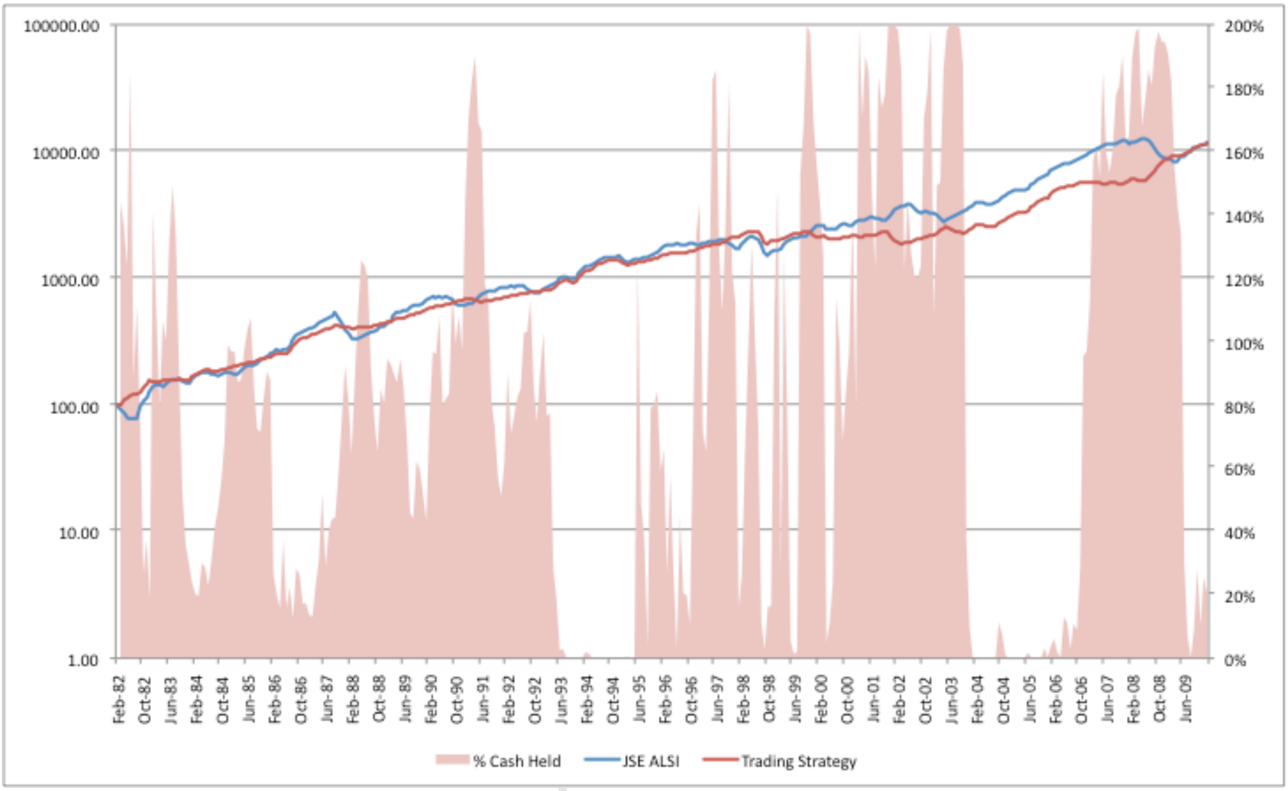
Figure 8.7 Cumulative Value of 7-Year Rolling Window Model 3-Month Trading Strategy C relative to the JSE ALSI



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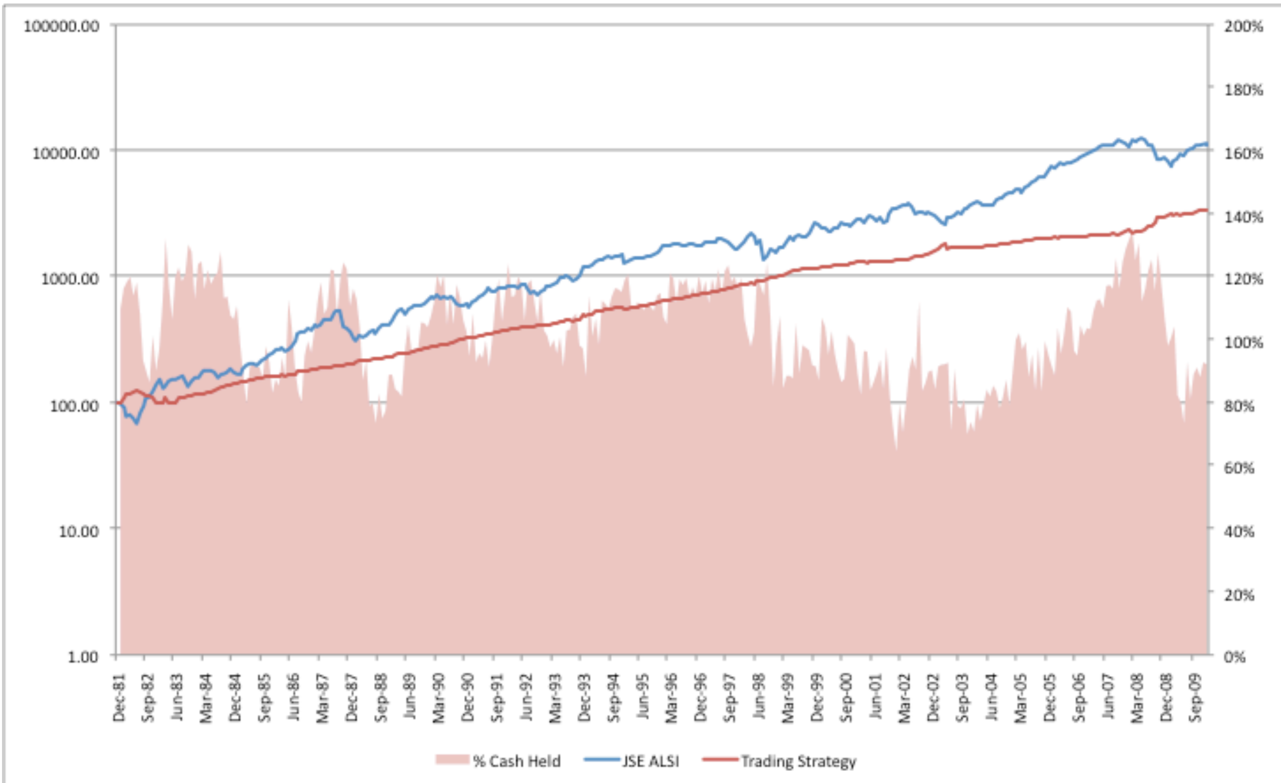
Throughout the time period, it is clear that there are periods of several years where the JSE ALSI has outperformed relative to the strategy, with this outperformance normally reversed over a short horizon when the JSE ALSI declines in value. Until 1999, the performance of a buy-and-hold strategy and that of the constructed trading strategy is almost identical, with the trading strategy generating its return with a smoother pattern. From this point on, there is a divergence, caused mostly in the early 2000s and between 2006-2008 when large short positions were taken in an appreciating market. However, the values of the trading strategy and that of a buy-and-hold strategy converge again after the sub-prime crisis, as trading strategy C strongly outperforms the declining market due to its large short position. Due to the construction of the portfolio, this similar magnitude of returns across the period can only occur when the forecasts provide the correct signals at a significant strength to allow for large positions to be taken. Sometimes the forecasts are incorrect, such as in 2003, leading to strong underperformance, but in general, the forecasts do provide some ability to profit from downturns. However, like all strategies based on these forecasts, the signal that the market is going to underperform tend to come several periods before the market underperformance occurs. In periods when the market direction is less certain, it also provides a downside buffer, as can be seen in 1988.

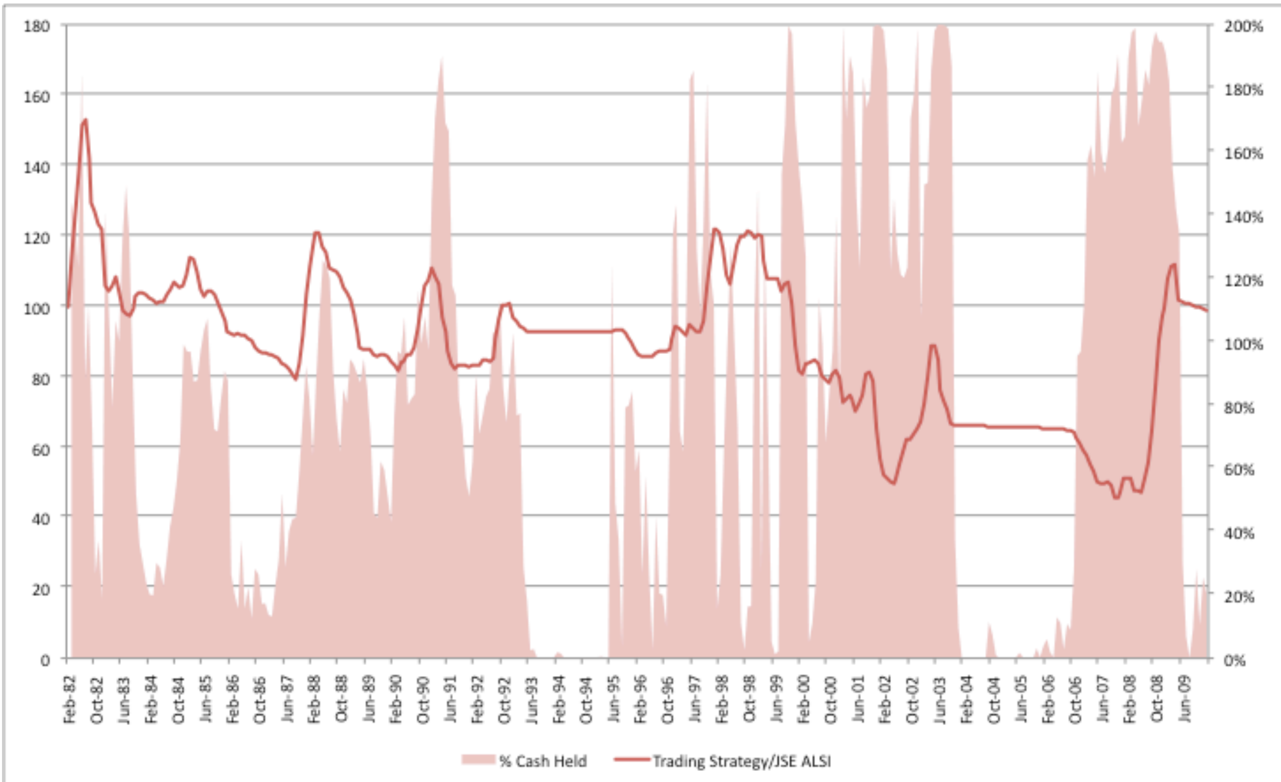
Figure 8.8 Cumulative Value of 10-Year Expanding Window Model 1-Month Trading Strategy C relative to the JSE ALSI



Apart from the initial few periods of this strategy, it consistently underperforms relative to the JSE ALSI, although the pattern of returns is stable throughout the time period. This is as a result of a lack of variability in forecasts. Therefore, the strategy is generally only slightly differently invested from a pure risk-free portfolio. As the JSE ALSI historically has generated a higher return than risk-free assets, albeit with higher volatility, the patterns of the buy-and-hold strategy and this variation of trading strategy C are to be expected. Even though this strategy also avoids market declines, the outperformance during these time periods is insufficient to recoup the value lost during the periods of underperformance, leading to the poor performance, in absolute terms, relative to the JSE ALSI, over the entire time period.

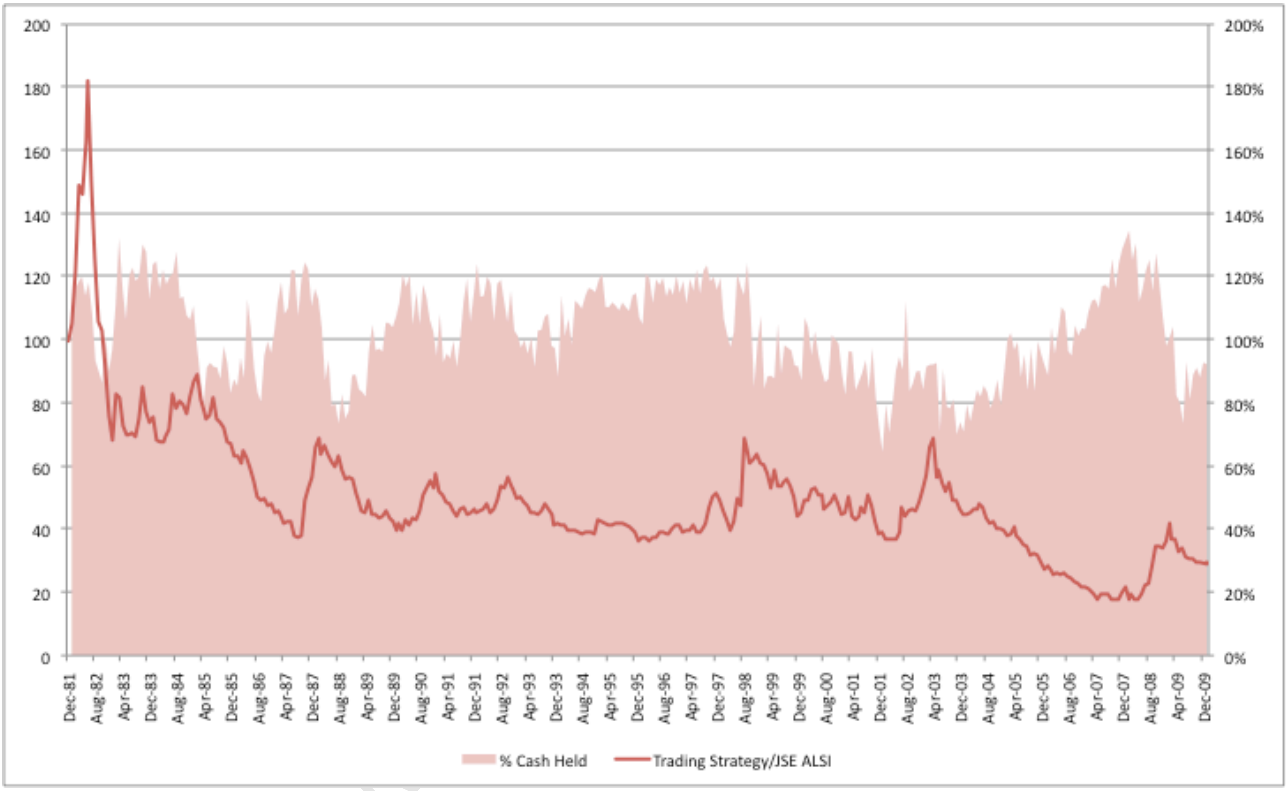
To more clearly illustrate the pattern of out and underperformance, the graphs below shows the value of the cumulative strategy values relative to the cumulative ALSI value.

Figure 8.9 Cumulative Outperformance of 7-Year Rolling Window Model 3-Month Trading Strategy C relative to JSE ALSI



The pattern of underperformance is generally not significantly large before 2000, and the years of underperformance tend to be reversed when the model switches to a short position of the JSE ALSI. However, after 2000, the strategy is in a short position against the JSE ALSI for 4 years, during a strong bull cycle. As a result, there is heavy underperformance, such that, even after the end of the bull period caused by commodity price increases, the strategy still does not reverse its previous relative loss. The strategy then fails to move out of its short position during the successive recovery, causing most of the value that is gained from the prior shock to be lost. However, the shift in 2006 to a short position, although leading to an initial underperformance, strongly outperforms during the subprime crisis, as the strategy does not only avoid the sharp decline in market value over the time period, but actively profits from it. Therefore, the pattern of outperformance varies across time period, with the last decade having the most volatile movements in relative value.

Figure 8.10 Cumulative Outperformance of 10-Year Expanding Window Model 1-Month Trading Strategy C relative to JSE ALSI



After the strong outperformance in the first year, the strategy strong underperforms. From 1983 until 1988, there is a period of underperformance followed by a temporary reversal. However, the outperformance is insufficient to recoup the value lost in the period of underperformance. From 1988 to 1999, the strategy underperforms (although the underperformance is fairly flat from 1995-1997), before outperforming during a market decline. This period of outperformance is sufficient to recoup the value lost over the previous eleven years. From 1999 to 2003, there is once again underperformance followed by a reversal, with the outperformance once again sufficient to recoup the value lost over the previous years of underperformance. However, from 2003 until 2009, the underperformance is larger than the outperformance during the subprime crisis, and the strategy therefore loses more value over this cycle. Since 2009, the strategy is once again underperforming, although its performance over the entire cycle cannot yet be gauged.

Conclusions

In removing certain sources of look-ahead bias, the predictive power of the model decreases substantially. Based on a regression analysis and hit-rate of the predicted against actual returns, it seems unlikely that any excess profits can be generated in implementing these models in trading strategies. However, the evidence from the trading strategies suggests that both excess returns and risk-adjusted returns can be generated through the use of a market-timing model. The excess absolute returns occur with certain specifications when using the 7 and 10-year rolling window specifications for short return horizons, and this suggests that these models are able to generate correct, strong signals on a sufficient number of occasions to generate excess returns.

The pattern of returns is also dependent on the choice of portfolio construction. Trading strategy A leads to the highest returns with the highest standard deviations, with trading strategy C displaying the inverse and trading strategy B providing a balance between the two. This finding is consistent with the strategies derived from the forecasts of the earlier models that did not account for look-ahead bias, increasing the robustness of this result.

It is also clear that utilising the trading strategy A for short return horizons based on the 7 and 10-year rolling window models generates excess returns, thereby indicating that this strategy may be applicable to a real-world investment environment. Trading strategy B also exhibits outperformance when forecasts generated from a 7-year rolling return are applied to a 3-month return horizon.

8.4 Applying Trading Costs

Although the above suggests that there is potential for excess returns by timing the market using a multifactor forecast model, it also assumes zero transaction costs. This is a naïve view and, in this section, this restrictive assumption is relaxed.

Only two combinations of the model and strategy are included. These are the returns generated using trading strategy A, a one-month holding period and specified using a 7-year rolling regression, and returns generated

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using trading strategy B, a three-month holding period and specified using a 7-year rolling regression. These two permutations are chosen because they a) outperform the market and b) their specification provide the best returns utilising their trading strategy. Trading strategy C is ignored, as no specification is able to outperform the market.

Three levels of transaction costs are applied: low, where transaction costs are 50bps; medium where transaction costs are 100bps; and high, where transaction costs are 150bps. The returns of each trading strategy with the differing transaction costs are tabulated below, as well as the returns of a buy-and-hold trading strategy. Transaction costs on the reinvestment of dividends are assumed to be zero for all cases. It is ignored because the cost payable on transactions is indeterminable without dividend data across the entire sample. As only the annualised dividend yields are available for the sample, this data is unknown. However, as the trading strategies are invested less in the JSE ALSI than the pure buy-and-hold strategy, they incur less transaction costs on reinvestment of dividends. Therefore, the returns of the trading strategies are slightly downward biased due to this assumption.

The returns, standard deviations and risk-adjusted returns (calculated as return divided by standard deviation) of the trading strategies with the various levels of transaction costs are tabulated below.

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Table 8.11 Returns on Trading Strategies with Transaction Costs

	1-Month Holding Period of Trading Strategy A with Transaction Costs	3-Month Holding Period of Trading Strategy B with Transaction Costs	JSE ALSI – One Month Sample Period
No Transaction Costs - Return	21.18%	19.38%	18.23%
No Transaction Costs - Standard Deviation	14.01%	15.07%	21.54%
No Transaction Costs – Risk-Adjusted Return	1.51	1.29	0.85
Low Transaction Costs (50bps) - Return	20.03%	19.16%	18.23%
Low Transaction Costs (50bps) - Standard Deviation	13.97%	15.07%	21.54%
Low Transaction Costs (50bps) – Risk-Adjusted Return	1.43	1.27	0.85
Medium Transaction Costs (100bps) - Return	18.88%	18.94%	18.23%
Medium Transaction Costs (100bps) – Standard Deviation	13.96%	15.08%	21.54%
Medium Transaction Costs (100bps) – Risk-Adjusted Return	1.35	1.26	0.85
High Transaction Costs (150bps) – Return	17.74%	18.72%	18.23%
High Transaction Costs (150bps) – Standard Deviation	13.98%	15.10%	21.54%
High Transaction Costs (150bps) – Risk-Adjusted Return	1.27	1.24	0.85

Risk-Adjusted Return is calculated as return divided by standard deviation. Bracketed figures indicate statistical significance of differences between trading strategy and JSE ALSI.

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The impact of transaction costs has a sizeable impact on the excess returns generated by the two market timing strategies. Trading strategy A provides the greatest return when no or low transaction costs are incurred, whereas trading strategy B provides the greatest return when medium or high transaction costs are incurred. More interesting is that trading strategy A underperforms relative to the market when high transaction costs are incurred. However, this result is not unexpected. As trading strategy A incurs transaction costs on its entire value when it switches from the market to the risk-free asset and vice versa, transaction costs will impact it to a greater degree than that of trading strategy B, where only the percentage change in asset allocation leads to transaction costs being incurred.

Across the selected strategies and model specification, the level of risk taken on by the investor is substantially lower than that of a pure buy-and-hold strategy. Therefore, it is clear that, in the majority of cases, an investor can generate returns in excess of a pure buy-and-hold strategy in the JSE ALSI at lower risk. This reflects in the risk-adjusted return, which is consistently higher than a pure buy-and-hold strategy in the JSE ALSI.

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9 Conclusions

In spite of the efficient market hypothesis of Fama (1970), there is evidence that market returns are both predictable and exploitable. Much of this predictability finds theoretical support from the discussion in the literature review relating to behavioural finance, where sufficient numbers of investors have predictable heuristics, such that anomalies from the rational efficient market are possible. Substantial empirical work, also presented in the literature review, finds evidence that valuation measures, such as earnings and dividend yield, and growth measures are able to predict market movements.

This study, limited to a South African sample, attempts to expand on the literature by focusing on the relationships between potential predictor variables and returns of differing horizons (1, 3, 6, 12 and 24-month returns); the ability of multivariate models based on these relationships to successfully predict future returns; the returns and return characteristics that can be generated by utilising these forecasts in three trading strategies; the ability to exploit market predictability when replicating the methodology in a sample that is limited to only include information available at each point in time; and, finally, by analysing the impact of transaction costs on strategy returns.

The initial correlation analysis provides evidence that there are statistically significant relationships between potential predictor variables and future returns. Earnings yield and a measure of long-term historic returns are positively and negatively correlated, respectively, and statistically significant across all future return horizons, while short-term returns and adjusted earnings yield are positively and significantly correlated with future short-term return horizons. Certain measures of long-term earnings growth are negatively and significantly correlated with future long-term returns. Most short-term historic returns and all short-term overbought/sold indicators are all positively and statistically significantly correlated with 1-month returns, while certain measures of long-term historic returns and a long-term overbought/sold indicator is negatively and statistically significantly correlated with future returns of a horizon equal to or

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longer than 6 months. However, deviations from long-term price/earnings are not significantly correlated with any return horizon, nor are, more surprisingly, dividend yield and term spread variables.

The findings of long-term historic returns and overbought/sold indicators imply a long-term mean reversion, while their short-term equivalents indicate a short-term momentum effect, as expected based on the theory of, and empirical evidence supporting, behavioural finance. The positive earnings yield provides support to the notion that forecast returns are possible due to changes in required rates of returns, as expected based on Gordon's dividend discount model. However, the negative relationship between long-term historic earnings growth and future long-term returns appears to be contradictory to the model. There are two potential explanations: that the model is invalid, or that growth is mean-reverting and that investors expect periods of high growth to be followed by low growth, and vice versa. In a theory that is alternative to the dividend discount model, it is possible that the earnings growth variable is capturing movements in long-term business cycles.

The significant independent variables are tested for their suitability in an ordinary least squares regression estimation by ensuring that the variables are stationary, without a structural break and not too heavily correlated with other independent variables. The variables are all found to be stationary and most show a relationship, based on a visual analysis, with the JSE ALSI, with a relationship not being able to be determined with noisy, short-term variables. Analysis of the variables' means and standard deviations, and their correlations with the relevant future return horizons, broken into two sub-samples, finds initial evidence of a structural break. However, an ordinary least squares regression analysis incorporating dummies for a potential structural break finds no statistically significant evidence of a structural break. Although there is evidence of multicollinearity amongst independent variables, no correlation is considered great enough to merit exclusion from the study.

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Finally, a cointegrating relationship between the JSE ALSI and earnings, interest rates, commodity prices and exchange rates is established and the residual is found to be statistically significant with all future returns, irrespective of the return horizon.

With the establishment of relationships between predictor variables and future returns, multivariate regression models are estimated for each return horizon. These forecasts are then transformed into a possibility of a positive return and utilised in three trading strategies: A, a pure switch between risky and risk-free asset based on a cut-off of 50%; B, a weighting between the two assets dependent on the strength of the prediction; and C, a movement between long and short positions in the JSE ALSI dependent on the strength of the prediction. Although the R^2 and hit-rates for the forecasts are low and appear to suffer from forecast bias, trading strategy A is able to outperform the market in excess of 4.5% per annum. Although certain combinations of return horizon and trading strategy yield lower absolute returns, on a risk-adjusted basis, the forecast model and their trading strategy outperforms the JSE ALSI.

An additional variable is then included, termed the implicit forecast, which transforms longer-term forecasts into predictors for shorter-term forecasts. The inclusion of these forecasts leads to higher R^2s and hit-rates and lower forecasting biases, and also to increases in both absolute and risk-adjusted returns, with the exception of trading strategy C, which has lower risk-adjusted returns for 1, 3, and 6-month returns horizons. The best performing strategy (strategy A) is able to outperform the market by 6% per annum.

However, the above methodology includes all available observations in its sample. This leads to two look-ahead biases: the first being that the estimated coefficients will be biased because they derive their relationship from observations not available at each point in time; and the second being that the model specification, based on the strength of correlation between potential variable and future return, also includes information that is unavailable at each point in time. To overcome this, the methodology is replicated using a limited sample of data, all available at each point in time, which updates as new observations are included in the sample. Four different

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specifications, 5, 7 and 10-year rolling window regressions and a 10-year expanding window regression, are estimated for thoroughness.

The removal of the look-ahead bias has a substantial impact. The hit-rates for most return horizons and specifications are lower than that of the benchmark, with the exception of 3-month return horizons estimated with 7 and 10-year rolling regressions and 6 and 12-month returns estimated with the 10-year expanding window horizon. Absolute outperformance of the best combination of trading strategy, model specification and return horizon only yields outperformance of slightly less than 3% per annum. However, across most combinations, the use of market forecasts leads to higher risk-adjusted returns relative to the JSE ALSI.

Finally, the impact of trading costs is analysed. Using the best absolute performing combination of the first and second trading strategies (the third is excluded as all combinations underperform, in absolute terms, relative to the JSE ALSI), three costs are applied to all transactions: low, defined as 50bps of the transaction value; medium, defined as 100bps of the transaction value; and high, defined as 150bps of the transaction value. For low transaction costs, trading strategy A still outperforms the market and the trading strategy B by roughly 1.8 and 0.9% respectively. However, with medium and high transaction costs, trading strategy B yields the greatest outperformance (roughly 0.7% and 0.5% per annum respectively), with trading strategy A underperforming relative to the JSE ALSI when high transaction costs are assumed.

In conclusion, there is empirical evidence that a quantitatively based decision process utilising available public information is able to provide timing insights that lead to outperformance relative to the JSE ALSI. There is also evidence to suggest that this outperformance persists in the presence of trading costs. However, the choice of model specification, return horizon and trading strategy leads to significantly different returns and it is possible, due to the large number of potential combinations, that this result is due to data snooping and not due to a viable forecasting strategy.

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Although this study has attempted to be as comprehensive as possible, there are at least three possible ways in which it can be extended. The first is to include more potential predictor variables. The inclusion of more variables will allow for more potential relationships to be uncovered and utilised in the forecast generating process. The second is to extend the methodology used to proxy the investing decision into the cointegrating relationship. In this study, it is assumed to be constant through time, thereby potentially ignoring evidence suggesting that a superior relationship may exist at each point in time. Allowing it to vary and update dependent on the strength of relationships at each point in time will create a more thorough analysis. The third is to investigate the ability of each model specification to outperform the market recursively. Thus, at point t, the out-of-sample performance of each combination of model specification, return horizon and trading strategy could be analysed, with the prediction derived from the best historic performing model implemented at that point. With the incorporation of these changes, all possible relationships would be considered and all possible look-ahead biases eliminated, providing a more clear answer as to whether market predictability exists and is exploitable.

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