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Value and momentum portfolios on the Johannesburg Stock Exchange

Paolo De Grandis

A research report submitted to the Faculty of Commerce, Law and Management, University of the Witwatersrand, in partial fulfilment of the requirements for the degree of Master of Business Administration

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ABSTRACT

The existence and persistence of the mean reversion and value effects on equity markets suggest that it may be possible to use these phenomena to identity commercially exploitable arbitrage opportunities. This research attempted to capitalise on such irrational investor behaviour on the Johannesburg Stock Exchange by developing market-beating trading strategies founded on the theories of mean reversion and value investing, both individually and in combination. Historical share price, dividend payouts, price-to-earnings and book-to-market data were used to generate test portfolios that were optimised in terms of excess returns over the three variables formation period, holding period and portfolio size. The results of the optimisation simulations revealed significant opportunities to generate market-beating returns for all trading strategies tested. Mean reversion trading strategies were shown to outperform price-to-earnings and book-to-market strategies. The incorporation of price-to-earnings and book-to-market constraints into the mean reversion strategies proved to reduce the effectiveness of those strategies.

DECLARATION

I, Paolo De Grandis, declare that this research report is my own work except as indicated in the references and acknowledgements. It is submitted in partial fulfilment of the requirements for the degree of Master of Business Administration in the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination in this or any other university.

Paolo De Grandis

Signed at ……

On the …….. day of …… 2013

ACKNOWLEDGEMENTS

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- Max MacKenzie for helping me identify and develop a research topic;
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CHAPTER 1: INTRODUCTION

1.1 Purpose of the study

The purpose of this research is to identify commercially exploitable arbitrage opportunities that an investor could use to earn market-beating returns on the Johannesburg Stock Exchange. The report attempts to expose investor overreaction on the Johannesburg Stock Exchange (JSE), and establish whether is possible to create market-beating trading strategies founded on the theories of mean reversion and value investing individually, as well as a combination of these theories.

1.2 Context of the study

Finding the optimal trading rule or leading indicator has long been the goal of those who believe that the markets are inefficient and pubic information, be it price information or measures of a firm's intrinsic value, could be used to predict future share price movement.

The efficient market hypothesis (EMH) proposes three levels of market efficiency. In its strong form, efficient market prices quickly reflect all information, even hidden or insider information. The semi-strong form EMH claims that prices reflect all publicly available information, and that prices quickly change to reflect new public information. In a weak-form efficient market, prices on traded assets already reflect all historical price information (Fama, 1970). Investigations have generally found major stock markets to be weak-form efficient (Basu, 1977; Chan, Hamao, & Lakonishok, 1991; De Bondt & Thaler, 1985; De Bondt & Thaler, 1987; Fama & French, 1992; Nicholson, 1968; Rosenberg, Reid, & Lansteiu, 1984).

The apparent existence of irrational investor behaviour as evidenced by mean reversion challenges market rationality. Markets seem to react swiftly to new information, as semi-strong and weak-form efficiency would predict. However, it is often found that the magnitude of these reactions are greater than the theory

predicts they should be. Investors overreact to recent information, and it can take some time for the market to correct for this overreaction, that is, for market prices to revert back to their "true" value. The result of this behaviour is short-term momentum in share prices in one direction, followed by longer-term correction or reversion to the mean. This process is represented in Figure 1.

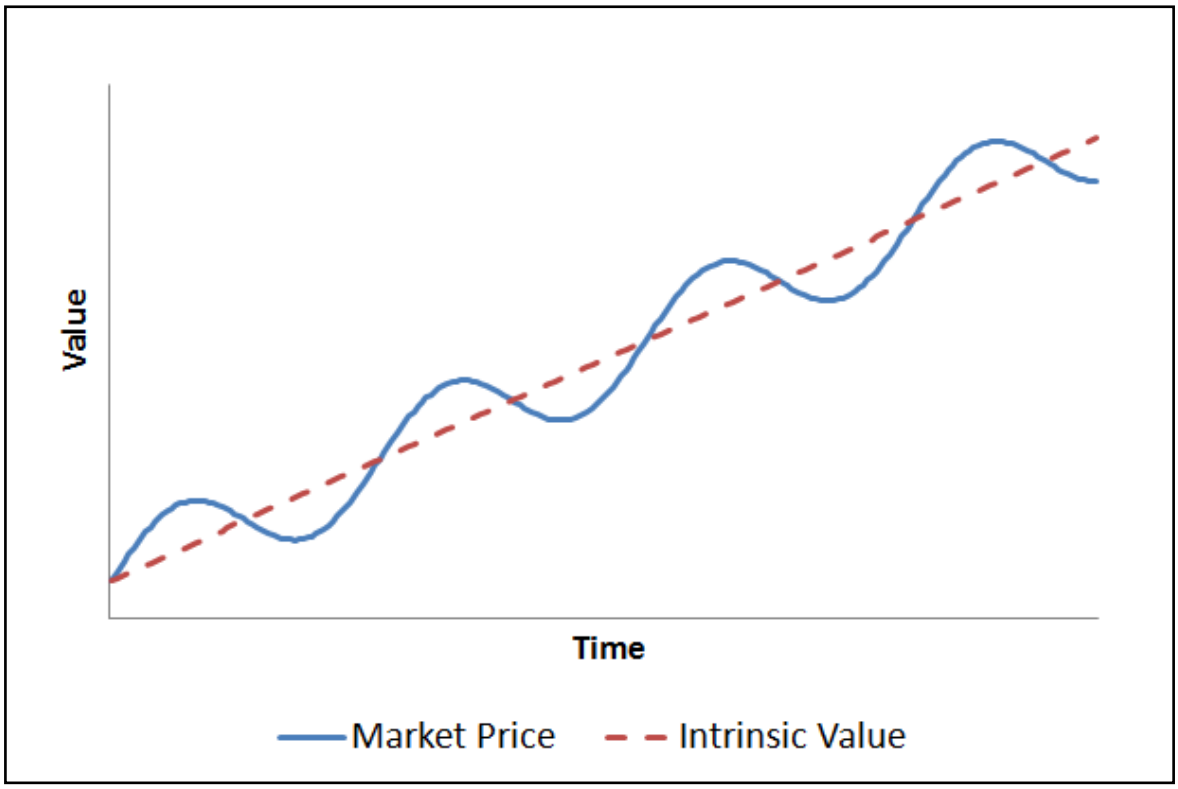


Figure 1: Share price fluctuation around the share's intrinsic value

The fact that this irrational investor behaviour exists is very exciting for both technical analysts and value investors because it suggests that, if it is possible to accurately assess the timing surrounding these trends, an investor could outperform the market by buying shares when they are priced low, riding the momentum beyond the intrinsic value, and then selling the shares before the market corrects.

This concept is represented graphically in Figure 2. Buying the share when its price is furthest below its intrinsic value and selling it when its prices is furthest above its intrinsic value will generate maximum absolute returns; (in later chapters this will be referred to as a loser strategy). That said, it is also possible to generate lesser positive returns by buying the share as the price is

on an upwards trajectory relative to the shares intrinsic value, and selling it when or before it reaches its furthest point above the intrinsic value; (this will be referred to as a winner strategy).

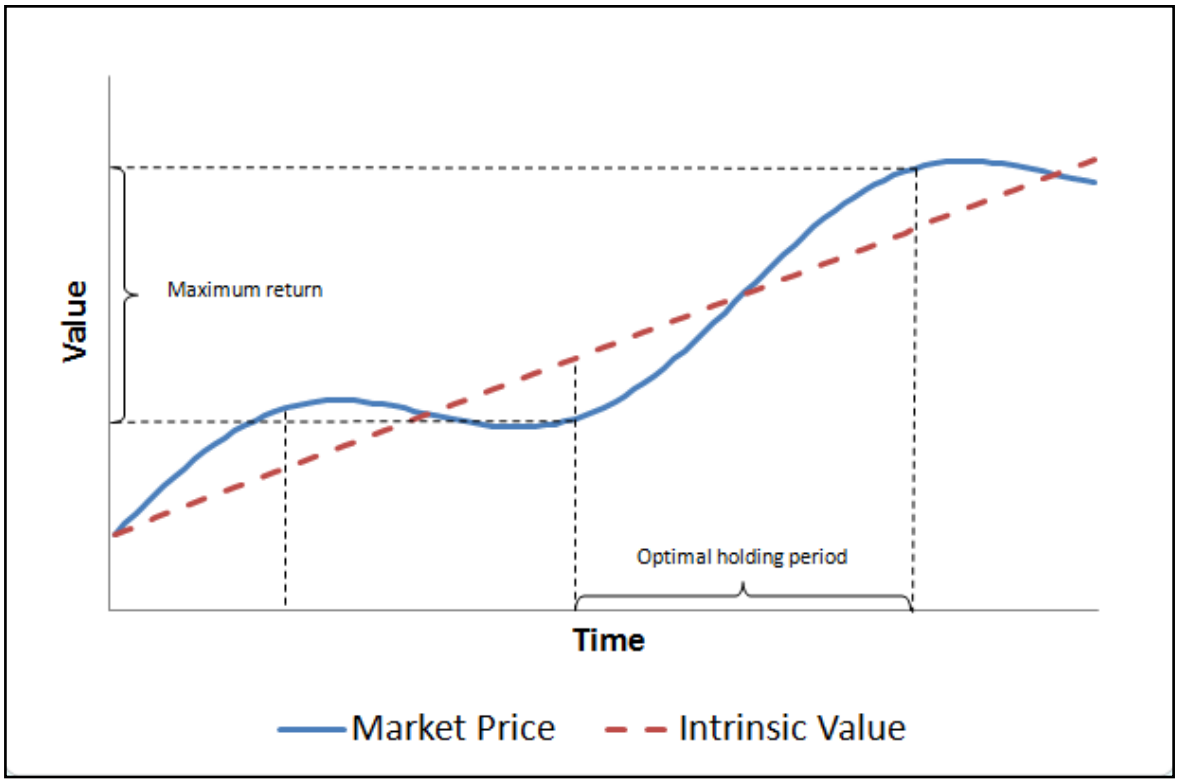


Figure 2: How to extract maximum profit from mean reversion

Many attempts have been made to explain the causal factors surrounding mean reversion market trends. These have been examined in detail in the literature review.

When it comes to investing on the stock market, two of the most recognised investment paradigms are technical analysis and value investing: technical analysts attempt to identify trends in order to predict future share price movements, and value investors try to identify shares that appear to be under-priced by some sort of fundamental analysis. Mean reversion of share prices, as explained above, clearly falls into the ambit of technical analysis, however, the essence of this strategy is not all that different to that of a contrarian value investing trading strategy. In both cases the idea is to buy when the market value is below the intrinsic value, and sell when the market value is above the intrinsic value. The key difference between the two approaches is the measure

that is employed; namely the share price in the case of mean reversion trading strategies, and one or more value measures (such as the price-to-earnings ratio) in the case of contrarian value investing trading strategies.

The similarities across the two investment approaches suggest that there may be a way to create a market-beating trading strategy by combining elements from both approaches, and it is the intention of this research to do just this. The research attempts to incorporate trading rules relating to two of the most commonly used value investing measures, namely the price-to-earnings (P/E) ratio and the book-to-market (B/M) ratio, into a mean reversion trading strategy, in the hope that such a combined strategy would realise returns greater than those realised by a pure mean reversion strategy.

1.3 Problem statement

1.3.1 Main problem

Could a trading strategy founded on the theories of mean reversion and value investing be used to outperform both the market and trading strategies designed to exploit mean reversion of prices exclusively?

1.3.2 Sub-problems

First sub-problem: Could a trading strategy that exploits mean reversion of share prices be used to create a portfolio that outperforms the market?

Second sub-problem: Could a value investing trading strategy be used to create a portfolio that outperforms the market?

Third sub-problem: Could the incorporation of value investing principles into a mean reversion trading strategy result in a trading strategy that outperforms a pure mean reversion trading strategy?

1.4 Significance of the study

The significance of the study is fourfold:

Firstly it contributes to the body of research on mean reversion and value investing in a South African context. The study fills a gap in that most of the existing research in this field is conducted in markets in the United States. Where research takes place in international markets, it focuses primarily on developed countries. Very few studies have attempted to apply these theories to the South African market.

Secondly, the research tested whether previous results still hold. This research roughly replicated and built on the work of Muller (1999) who, using data from the JSE, successfully compiled a loser portfolio that outperformed one of recognised winners as well as the market index. More than a decade has passed since this study was conducted. Given that the widespread application of a particular trading rule tends to reduce the benefits realised from using that rule, there was value in repeating the study to establish whether the results would still hold. Even if it was found that overreaction still existed on the JSE, the extent to which it occurs and the optimal trading rules that exploit its existence may have changed significantly in the last decade.

Thirdly, the results of the research have implications with respect to the application of the efficient market hypothesis to the JSE. Any indication of irrational investor behaviour provides evidence against market efficiency.

Finally, to the author's knowledge no attempt has ever been made to improve a mean reversion strategy by using value measures to selectively exclude individual shares from the set of shares that may be purchased. (The method of scaling P/E and B/M ratios by the industry median was also devised by the author, however, given its simplicity, the author would not be surprised to find out that it had been employed in previous research).

The study aims to identify commercially exploitable arbitrage, and as such, it provides guidance to investors on the JSE who wish to earn market-beating returns.

1.5 Delimitations of the study

This study attempts to establish whether it is possible to identify trading rules, based on the theories of both mean reversion of prices and value investing, that can be used to realise market-beating returns on the JSE.

The research focuses exclusively on shares traded on the JSE. There are no limitations to any particular sector.

Before testing combined trading strategies, the study first investigates the effectiveness of mean reversion and value investing trading strategies in isolation.

In the case of value investing, the study tests whether scaling a share's value measure by the relevant industry median (i.e. making value measure comparisons that are industry specific, as opposed to simply using the value measure to rank a share against the entire market) improves the returns generated by these trading strategies; this is done in an attempt to maximise trading strategy returns prior to any attempts to create a combined strategy.

Even though the research problem specifically refers to value investing, for the sake of comparison and in order to facilitate interpretation of the combined strategy results, both growth investing and value investing strategies are tested. (For the purposes of this research a growth strategy is the equivalent of a mean reversion winner strategy, and a value strategy the equivalent of a mean reversion loser strategy).

The two value measures tested are the P/E ratio and the B/M ratio. Each of these measures are tested in isolation: no attempt is made to create trading rules that incorporate a combination of these two measures.

The literature review in Chapter 2 discusses behavioural psychology and some of the ways in which investor behaviour has been shown to be irrational, however, should evidence of irrational behaviour be found, no attempt will be made to isolate or explain the causal factors. Such an understanding of the causes is not required for a trading strategy to be useful.

The study attempts to confirm previous findings relating to investor overreaction on the JSE, but does not explicitly attempt to establish whether or how investor behaviour has changed over time, though some comparisons are made to the results of prior research.

The results of this study are not necessarily extendable to all financial markets.

1.6 Definition of terms

- Book-to-market ratio – a way of measuring the relative value of a company by comparing its net asset value (i.e. its accounting value) to its share price (i.e. its market value).

- Cognitive bias - the tendency to make errors in judgement and decision making even when factual and rational evidence should lead to a different judgement or decision.

- Contrarian trading strategy - a trading strategy in which an investor buys or sells specific investments when the majority of investors appear to be doing the opposite, to the point where that investment has become mispriced (Chan, 1988).

- Data snooping bias - a form of statistical bias generated by the misuse of data mining techniques. When large numbers of tests are performed it is always expected that some will produce false results, so the risk exists that that those using data mining techniques may be misled by these apparently significant results, even though they are mere products of random variation. The bias is particularly prevalent when a large number of hypotheses are automatically tested on a single data set by exhaustively searching for combinations of variables that might show a correlation (Lo & MacKinlay, 1990).

- Equity style – an investment belief that a group investors expect will add value when followed (Christopherson & Williams, 1997). Examples of equity styles on the JSE include the December effect (Bradfield, 1990) and the public holiday effect (Bhana, 1994).

- Excess returns – see “market-beating returns”.

- Fundamental analysis (in the context of share valuations) – a method of valuing a share that aims to give an estimate of the intrinsic value of the share, based on predictions of the company’s probable future cash flows. Fundamental analysts attempt to study everything that could reasonably be expected to affect the share’s value, such as the company’s financial data, management, business prospects and competition.

- Growth investing – buying shares of companies that are expected to grow at above average rates, even if the share price appears expensive in terms of value metrics such as the P/E ratio.

- Market-beating returns - returns greater than those realised by the market as a whole over the same period.

- Modern portfolio theory – a theory of investing that seeks to construct an optimal portfolio that maximises expected return for a given amount of portfolio risk. The theory emphasises that risk is an inherent part of higher reward.

- Price-to-earnings ratio – an equity valuation measure defined as the ratio of a share’s current price to its per-share earnings over the past year.

- Public holiday effect – the trading day prior to a public holiday tends to exhibit higher than average returns (Bhana, 1994).

- Trading strategy - a predefined set of rules for making trading decisions.

- Technical analysis - an investment discipline where the direction of prices is forecast through the study of historical market data, primarily price and volume.

- Value investing - value investing generally involves buying shares that appear under-priced by some form of fundamental analysis, with the expectation that these share will outperform the market as a whole (Auret & Cline, 2011).

1.7 Assumptions

The research attempts to identify trading strategies that successfully exploit mean reversion theory and create portfolios that realise market-beating returns when mispriced shares ultimately revert back to their true values (a.k.a. intrinsic values or means). The implication is that if the true value of a particular share changes in the period under study, the share price will instead revert to a new, possibly different mean, and the result would be meaningless. Therefore it is assumed that shares intrinsic values do not change during the sample period.

Previous research has found optimal holding periods in mean reversion trading strategies on the JSE to be in the order of one to two years (Muller, 1999). Given that the sample used in this research will exclude small companies (as the sample will comprise the top 200 companies on the JSE by market capitalisation), it is reasonable that the underlying value of a company in the sample (and therefore the underlying values of that company's shares) will not change quickly enough to invalidate the results.

It is also assumed that investor behaviour does not change over the short- to medium-term. If, for example, investors tendency to overreact to new information were to diminish over time, then the results of this study would be less conclusive and would not be a good predictor of future investor behaviour. Ultimately it would reduce the chances of being able to use the findings of this research to create trading strategies that will realise market-beating returns.

It is not unreasonable to assume that the turbulent economic environment resulting from the 2008 global financial crisis could have caused investors to change their trading behaviour. That said, even if trading strategies changed following the crisis, it is not known how investors' tendency to overreact to new information would have been affected. Ironically it is only when the results of this research are compared to previous similar studies that one can gauge whether the assumption of consistent investor behaviour over time is reasonable or not.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

This section contains a literature review on the key themes of relevance to the study. It starts by looking at the efficient market hypothesis, which depending on the form that it takes, has implications for the possibility of identifying a trading strategy that can achieve market-beating returns. It then examines mean reversion and some of the behavioural finance attempts to explain its existence, followed by value investing, and the two value measures that will be employed in this research. Finally it reviews the relationship between mean reversion and value analysis, as well as prior attempts to use a combination of the two approaches to increase predictive power. The section concludes with an overview of the key learnings.

It should be noted that the similarities between mean reversion of share prices and contrarian value investing trading strategies have resulted in previous authors sometimes using the term "mean reversion" in the context of value investing. For example, Cubbin, Eidne, Firer and Gilbert (2006) define the tendency for shares with low P/E ratios to outperform their high P/E counterparts over the medium to long-term as mean reversion. To avoid confusion this author will only use the term "mean reversion" in the context of share prices.

2.1.1 Efficient Market Hypothesis

Since the work by Fama (1965, 1970) the Efficient Market Hypothesis (EMH) has become a central part of finance theory. The EMH asserts that one cannot use information available at the time an investment is made to consistently achieve returns in excess of average market returns on a risk adjusted basis.

Fama (1970) states three forms that the EMH can take, each dealing with different information and each having different implications for how markets work:

- The strong form of the EMH states that an equity market efficiently factors all information into accurate security prices so that no information of any kind, public or private, will help investors achieve market-beating returns.
- The semi-strong form of the hypothesis states that equity markets accurately process all publicly available information, such as companies' announcements or annual earnings figures. This implication of this form of the EMH is that fundamental analysis would be rendered useless as a means of identifying buy or sell opportunities, as there would not be any under or over-valued securities in an efficient market.
- The weak form of the EMH states that all historical market prices and trade volume information is already factored into security prices, so technical analysis could not be used to determine future prices.

Empirical evidence is mixed, but generally does not support the strong form of the EMH (De Bondt & Thaler, 1990; Fama, 1965, 1970; Roberts, 1959; Summers, 1986; Summers & Poterba, 1988). The most consistent evidence against the EMH is that shares with low P/E ratios (and similarly, high B/M or price-to-cash-flow ratios) tend to outperform other shares (Basu, 1977; Chan, et al., 1991; Fama & French, 1992; Nicholson, 1968; Reid, 1998; Rosenberg, et al., 1984). Market rationality is also challenged by De Bondt and Thaler (1985; 1987). De Bondt and Thaler identify "loser" shares that have experienced poor returns over some number of past years and "winner" shares that experienced high returns over a similar period to find that over the following period the loser shares experience higher average returns than the winners.

As one would expect, the bulk of EMH evidence is from developed markets in Europe and the United States. Less is known about the efficiency of emerging markets, especially those in Africa (Groenewold & Ariff, 1998). African stock markets are extremely small by world standards, so obtaining data series of sufficient frequency and duration to perform tests of market efficiency proves

challenging. South Africa dominates the African stock markets in terms of both size and sophistication, so unsurprisingly the majority of studies relating to market efficiency in Africa were conducted on the JSE (Smith, Jefferis, & Ryoo, 2002).

From a South African point of view, the majority of the evidence points towards the JSE being weak-form efficient. Several studies have found JSE indices to follow a random walk, implying that investors would not be able to consistently earn abnormal returns (Magnusson & Wydick, 2002; Ntim, Opong, Danbolt, & Dewotor, 2011; Smith, et al., 2002). Studies have also found empirical evidence for weak-form efficiency in the behaviour of share prices after public announcements are made, such as management buyout announcements (Bhana, 2005), share repurchase announcements (Bhana, 2007) and earnings announcements (Mlonzi, Kruger, & Nthoesane, 2011). When testing for changes in weak-form efficiency over time, Jefferis and Smith (2005) find the JSE to be weak-form efficient throughout the period January 1990 to June 2001. Mbululu and Chipeta (2012) conclude that the JSE is weak-form efficient when they fail to find evidence of the day-of-the-week effect on the JSE.

Evidence to the contrary is provided by Appiah-Kusi and Menyah (2003) who, using an autocorrelation test that acknowledges the possibility of non-linearity in the return generating process and adjusts for thin trading, conclude that the JSE is not weak-form efficient.

With regard to this research, it clearly follows that any evidence that a mean reversion trading strategy could be used to achieve market-beating returns would challenge the EMH in its weak form, and any evidence in support of value measures being used to achieve market-beating returns would challenge the EMH in its semi-strong form.

2.2 Technical analysis

The first part of this research attempts to, using mean reversion theory, identify trends in historical price patterns, and use these to create a trading strategy that outperforms the market. As this entails using time series share price information to predict future movement, this falls into the domain of technical analysis.

2.2.1 Mean reversion theory

Mean reversion in the context of share returns, (also sometimes known as mispricing-correction hypothesis, fads hypothesis or overreaction), is the tendency for share prices to overshoot and subsequently revert back to their true values, resulting in alternating periods of above-average and below-average returns.

Mean reversion was first identified by De Bondt and Thaler (1985). As explained previously, the authors formed portfolios of the best performing and the worst performing shares over a three year formation period (i.e. the "winners" and the "losers"). They found that their loser portfolios tended to achieve higher returns in the three to five years following their formation than the winner portfolios. De Bondt and Thaler (1985; 1987) argue that the observed results were due to shareholder overreaction and the subsequent reversion of share prices to their mean (i.e. the prices of the losers recovered after they had become too cheap, and the winners experienced lower returns after they had become too expensive).

Over the years several other international studies have also put forward evidence confirming the existence of mean reversion (Bauman, Conover, & Miller, 1999; Bessembinder, Coughenour, Seguin, & Smoller, 1995; Chan, et al., 1991; Dreman & Berry, 1995; Fama & French, 1992; Gropp, 2004; Jegadeesh & Titman, 2001; La Porta, 1996; La Porta, Lakonishok, Shleifer, & Vishny, 1997; Otchere & Chan, 2003; Power & Lonie, 1993; Rouwenhorst, 1998). The research in a South African context, though relatively sparse, has

yielded similar results (Bradfield & Ardington, 1997; Muller, 1999; Muller & Ward, 2012; Page & Way, 1992).

Muller's (1999) work in particular provides compelling evidence that it may be possible for an investor for create a market-beating mean reversion trading strategy on the JSE. Like De Bondt and Thaler (1985), Muller's approach entailed creating winner and loser portfolios based on historic share prices, however, having computing power on his side, Muller was able to optimise these portfolios to produce a maximum return in terms of formation period, number of shares in the portfolio and holding period. His results supported the case for the existence of arbitrage opportunities at both ends of the winner/loser continuum; his winner and loser strategies provided excess market returns of 15% and 20% per annum respectively.

It has been argued that that relative under and over performance in tests for mean reversion can be explained by the size effect (i.e. the tendency for small firms to outperform large firms). Zarowin (1989, 1990) found that when firms of different sizes are compared, smaller winners outperform larger losers. Similarly, Clare and Thomas (1995) found no evidence of long-run mean reversion when they controlled for firm size. Evidence to the contrary (showing that at least some mean reversion is evident, even after controlling for firm size) is put forward by several authors (Albert Jr & Henderson Jr, 1995; Chiao & Hueng, 2005; Chopra, Lakonishok, & Ritter, 1992; De Bondt & Thaler, 1987; Lakonishok & Shleifer, 1994).

It has also been argued loser shares bear higher fundamental risk of some sort, and that their higher average returns are simply compensation for this risk (Ball & Kothari, 1989; Chan, 1988; Fama & French, 1992). Despite the above claims being in neat accordance with modern portfolio theory, there is ample evidence to suggest that the outperformance cannot be explained by higher risk alone (Chopra, et al., 1992; De Bondt & Thaler, 1987; Lakonishok & Shleifer, 1994; Zarowin, 1990).

Given the evidence supporting the existence of mean reversion, it may be possible to create a market-beating trading strategy based on the theory. Muller (1999) identified such a strategy for trading on the JSE, and more recently Hsieh and Hodnett (2011) found evidence of investor overreaction on the JSE. However, given the evidence that stock market overreaction isn't consistent over time (C. R. Chen & Sauer, 1997) and that momentum strategies on the JSE do not consistently outperform the market (Bartens & Hassan, 2010), being able to identify such a trading strategy more than a decade after Muller (1999) did the same is not a given.

2.2.2 Behavioural finance

The field of behavioural finance attempts to explain why market participants make systematic errors affecting prices and returns, and resulting in market inefficiencies. The cognitive biases highlighted by behavioural finance are considered by technical analysts to be the theoretical basis for technical analysis.

Much of the most important research into cognitive biases that emerge when investors are faced with risk and uncertainty was conducted by Kahneman and Tversky (1972, 1973, 1977, 1979; Tversky & Kahneman, 1971, 1973). Based on their results they developed Prospect theory (Kahneman & Tversky, 1979), which sheds insights on how people make decisions between alternatives that involve risk. Prospect theory proposes that people react differently when faced with risks offering potential positive outcomes to those offering potential negative outcomes; Kahneman and Tversky (1979) find that people who are risk averse when positive amounts are at stake became risk-takers when the same choices involve losses.

Prospect theory challenges the notion of rational investors, implying that models such as modern portfolio theory and capital asset pricing model, which have investor rationality as an assumption, may not accurately predict how investors react to new information in reality.

Further to Prospect theory, many other pervasive behavioural finance effects have been identified that are inconsistent with the assumption of investor rationality. Some examples of these include the following:

- Availability bias – a person's evaluation of an event's probability is influenced by the number of occurrences of that event that are remembered and the ease with which they come to mind (Tversky & Kahneman, 1973).

- Loss aversion – people strongly prefer avoiding losses to acquiring gains (Tversky & Kahneman, 1991).

- Certainty effect – people prefer a sure gain to a much larger gain that is very likely but not certain (Kahneman & Tversky, 1979).

- Self-control – people or organisations who have trouble exercising self-control deliberately impose constraints on their future behaviour (Thaler & Shefrin, 1981).

- Sunk cost effect – people tend to continue an endeavour once an investment in money, effort or time has been made (Arkes & Blumer, 1985).

- Recency effect – people assign higher weightings to information that is fresh in their minds Investors over-weight recent information and under-weight long-term base data (De Bondt & Thaler, 1985; Kahneman & Tversky, 1973, 1977).

- Overreaction – investors overreact to recent relevant news (Poterba & Summers, 1988).

2.2.3 Hypothesis 1

H_0: An optimised mean reversion trading strategy will not outperform the market.

H_a: An optimised mean reversion trading strategy will outperform the market.

2.3 Value investing

Professors Benjamin Graham and David Dodd are credited with laying the foundation for value investing in their book “Security Analysis” (Graham & Dodd, 1934). In it they propose that a controlled investor could determine the rough value of a firm through diligent analysis of its financial statements, using the information to purchase under-priced shares and in this way earn a satisfactory return, while at the same time avoiding the risk of permanent losses.

These days such under-priced shares are better known as value shares or out-of-favour shares. Value shares tend to trade at a low price relative to their fundamentals, and are therefore considered undervalued by value investors. Value shares are generally identified by having a high ratio of a balance sheet or income statement measure of value to their market capitalisation (Basu, 1977). Growth shares, in contrast, are shares that are generally considered by investors to have significant growth prospects (Auret & Cline, 2011).

The value effect is said to exist when value shares provide a larger risk-adjusted return than growth shares (Robins, Sandler, & Durand, 1999). The value effect has been a popular area of research for many years, and the literature is flush with examples its existence, both internationally (Basu, 1977; Chan, et al., 1991; Davis, 1994; Fama & French, 1992; Jaffe, Keim, & Westerfield, 1989; Lakonishok, Vishny, & Shleifer, 1993; Rosenberg, et al., 1984) and in a South African context (Auret & Sinclaire, 2006; Basiewicz & Auret, 2009; Bhana, 1992; Graham & Uliana, 2001; Mutooni & Muller, 2007; Page & Palmer, 1991; Plaistowe & Knight, 1986; Van Rensburg & Robertson, 2003b).

Two of the most common means of identifying value shares are a low P/E ratio and a high B/M ratio. The second part of this research will attempt to use these ratios to create a contrarian trading strategy that outperforms the market.

2.3.1 Price-to-earnings ratio

The P/E ratio is a multifaceted measure of a firm's performance. It condenses many dynamics, including how the market perceives the level of a firm's earnings, and its future prospects. In theory, there are several problems with using historic P/E ratios as a predictor of future performance, such as:

- Investors are more concerned with future earnings than past earnings;
- The value of the ratio depends on the method of depreciation employed by the firm;
- The ratio does not reflect the level of risk incurred by the firm to achieve earnings; and
- Similarly, the ratio does not take into account the amount of capital employed by the firm (Firer, 1993).

In practice, however, the negative relationship between a firm's historic P/E ratio and its subsequent performance is well documented. Evidence of this negative relationship was first presented by Basu (1977). Basu studied the P/E ratios of U.S. shares and their subsequent performance over the period 1956 to 1971, and found that portfolios with low P/E shares exhibited higher returns than those with high P/E shares, even after adjustments were made for risk (proxied by the firms' betas). Several subsequent studies yielded similar results (Jaffe, et al., 1989) (Chan, et al., 1991) (Fama & French, 1992), confirming this P/E effect.

In a South African context, Page and Palmer (1991) were the first to identify a P/E effect on the JSE; they found that a portfolio of low P/E shares outperformed a portfolio of high P/E shares by 6.5% per year. When investigating style-based factors on the JSE, Van Rensburg and Robertson (2003b) found significant persistent P/E effects in the cross-section of returns. Wolmarans (2004) found that a small investor using an earnings yield[1] strategy could beat the market over the period spanning 1985 to 1998; this finding was later confirmed by Strugnell, Gilbert, and Kruger (2011). Employing a methodology similar to that of De Bondt and Thaler (1985), but using P/E ratios instead of historical returns to create winner and loser portfolios, Cubbin, Eidne, Firer, and Gilbert (2006) found that portfolios of high P/E shares underperformed significantly over five years against portfolios of low P/E shares. Similarly, Muller and Ward (2012) found evidence of a persistent earnings effect on the JSE; they found that over the period 1985 to 2011 their large earnings yield portfolio would have earned a premium of 13.4% per annum over their small earnings yield portfolio. Evidence to the contrary is provided by Auret and Cline (2011) who, after examining data from the period 1988 to 2006, found no evidence of a P/E effect.

Bailey and Gilbert (2007) argue that liquidity of shares may play a large role in explaining the persistence of the P/E effect. They test this assertion by extending the results of Cubbin, et al. (2006) and applying liquidity caps to the test portfolios. Bailey and Gilbert found that, although lessened, the P/E effect persisted after the application of the liquidity constraints. This result was later confirmed by Basiewicz and Auret (2010) .

It has also been argued that survivorship bias may play a role in explaining the persistence of the P/E effect. Gilbert and Strugnell (2010) updated Bailey and

[1] The PE ratio is frequently referred to in its inverted form, the earnings yield ratio. Earnings yield can be thought of as the cost to a publicly traded company of raising expansion capital through the issuance of shares, or as an estimate of the expected return from holding the shares (if we accept certain restrictive assumptions).

Gilbert's (2007) study by extending the period for a further 21 months and attempting to quantifying the impact of survivorship bias. They compared two separate groups of companies: a complete list of companies, and a list that were, at the time, still listed on the JSE. They found the effects survivorship bias to be present and material.

2.3.2 Book-to-market ratio

The B/M ratio (frequently referred to in its inverted form as the market-to-book ratio) is considered by many to be a proxy for unobservable common risk factors. Several authors consider the B/M ratio to be a proxy for a firm's default risk (Auret & Sinclaire, 2006; Fama & French, 1992; Vassalou & Xing, 2004). This line of thought led Fama and French (1993) to suggest that the extra return stemming from value stocks is simply compensation for their inherent systematic risk. According to Chen and Zhang (1998), the B/M ratio successfully captures three types of risk, namely distress of a firm, riskiness of a firm's cash flows and financial risk, and that property makes it a superior proxy for the value effect.

There is ample evidence in the literature supporting the existence of a B/M effect. Stattman (1980) found the average returns on U.S. stocks to be positively related to the B/M ratio. Rosenberg, et al. (1984) found that investors on the NYSE would have been able to earn abnormal returns by employing a B/M strategy (i.e. buying shares with a high B/M ratio and selling shares with a low B/M ratio). Chan, et al. (1991) and Fama and French (1992) broadened and developed these results: Chan, et al. (1991) identified a significant relationship between the B/M ratio and expected returns on the Japanese market; and Fama and French (1992) found that over the period 1963 to 1990, U.S. shares with a high B/M ratio significantly outperformed shares with a low B/M ratio, and that these differences in earnings could not be explained by differences their portfolios' betas. Daniel and Titman (1999) studied B/M ratios of firms and the relationship to mean reversion. They too found that high B/M portfolios persistently outperformed lot B/M portfolios, and attributed these findings to investor overconfidence generating a momentum effect, particularly

where the valuation of shares by investors required the interpretation of ambiguous information.

Plaistowe and Knight (1986) found evidence of a market-to-book effect on the JSE. They reviewed share data for industrial companies for the period 1973 to 1980, creating portfolios of “discount” companies (essentially high B/M ratio companies) and “premium” companies (essentially low B/M ratio companies). They then compared the average cumulative returns of the two portfolios to the returns of the RDM 100 Index. They found that the discount portfolios did not exhibit abnormal relative returns relative to the market, however, the premium portfolios did exhibit abnormal losses.

Further evidence of a B/M effect on the JSE is provided by several authors (Auret & Sinclaire, 2006; Basiewicz & Auret, 2010; Fraser & Page, 1999; Muller & Ward, 2012; Mutooni & Muller, 2007). Mutooni and Muller (2007) found that companies with low price-to-book (i.e. market-to-book) values outperformed companies with high price-to-book ratios over long periods of time, but that this outperformance was cyclical, with the inverse sometimes holding true. Muller and Ward (2012) found the price-to-book effect to be significant, but not persistent; their price-to-book portfolio performed well from 1999 to 2004, but subsequent to 2004 there was very little evidence that their price-to-book strategy continued to add value.

In addition to generally confirming the existence of a B/M effect on the JSE, the evidence also suggests that the B/M ratio is superior to other measures in explaining cross-section returns on the JSE. Auret and Sinclaire (2006) examined six style-based factors on the JSE, and found that though P/E and firm size were both positively correlated with returns, these effects were almost completely encompassed by the B/M effect. Basiewicz and Auret (2009), who found evidence of a value effect on the JSE after controlling for transaction costs and liquidity, also noted that the B/M ratio subsumed all other value indicators in multivariate regressions.

2.3.3 Hypothesis 2

H_0: An optimised value strategy that exploits the P/E effect or the B/M effect will not outperform the market.

H_a: An optimised value strategy that exploits the P/E effect or the B/M effect will outperform the market.

2.4 Combined trading strategies

The third part of this research attempts to combine technical analysis with value investing to create a trading strategy that is more effective than those that could be created by either technical analysis or value investing in isolation.

2.4.1 The link between momentum and value equity styles

Confusing use of terminology in the literature aside, the split between mean reversion of prices and the value effect is not always a clear one, and several authors have attempted to identify links between mean reversion of prices to value effects.

Haugen (1995) argues that the P/E effect can be attributed to overreaction on the part of investors; he claims that, though P/E ratios are able to predict earnings several years into the future, these predictions are mean reverting in nature because investors underestimate the influence of future competition in the underlying markets for goods and services when predicting earnings growth into the future.

Dreman and Berry (1995) and La Porta, et al. (1997) put forward evidence that investors overreact to earnings surprises, so that shares are not immediately priced at the appropriate level but instead revert to the mean over a period of years, and that this phenomenon is more significant for value shares.

Daniel and Titman (1999) studied the relationship between B/M values and mean reversion, and found that high B/M portfolio's outperformed the low B/M portfolios, and concluded that the momentum effect is likely to be strongest for

shares where investors need to interpret ambiguous information in order to value those shares, so abnormal returns are not attributable to risk.

Lee and Swaminathan (2000) put forward evidence that past trading volumes provide the link between momentum and value strategies; they found that past trading volumes could predict the magnitude and persistence of price momentum, as well as several characteristics associated with value investing, including (among others) earnings performance and B/M ratios.

2.4.2 Comparing equity styles

Once the existence of equity styles on the JSE had been generally accepted, the research turned its attention to establishing the effectiveness of different equity styles compared to each other and over time.

Van Rensburg (2001) used a cluster analysis to examine 20 style strategies on JSE industrial shares between 1983 and 1999, finding 11 of these to be statistically significant after adjusting for risk. His results suggested three style factors: earnings-to-price (value), market capitalisation (size) and the 12-month past positive returns (earnings-momentum).

When Van Rensburg and Robertson (2003b) extended this research using a cross-sectional regression methodology, they confirmed significant size and P/E effects, but found no momentum effect.

On the basis of these findings, Van Rensburg and Robertson (2003a) performed another study to examine the size and P/E variables in more detail. Looking at data from July 1990 to June 2000 using a two-way sorting procedure of quintile portfolios, they showed that that small size and low P/E shares both earned higher average returns, but with lower betas. Their results also suggested that to a large extent the small size and low P/E effects operated independently of each other, implying that a model of cross-sections of JSE returns should be based on at least two styles.

2.4.3 Combining equity styles

As one would expect, several studies have attempted to combine equity styles to identify to create more powerful predictors (and hence more effective trading strategies) that could be achieved with individual equity styles.

Frasier and Page (1999) investigated momentum and value strategies among industrial firms on the JSE. They found that both value strategies (based on B/M and dividend yield) and momentum strategies had the power to independently predict future returns, however, they found no evidence of interaction between the value and momentum effects; momentum strategies were not found to be stronger among value shares and vice versa.

Mutooni and Muller (2007) investigated style timing strategies on the JSE over the 20-year period ending 2006, and found that value shares outperformed growth shares regardless of size, however, potentially even greater returns could be achieved through carefully timed switches from a value style to a growth style and vice versa, especially when it came to shorter investment horizons. That said, the correct timing of these switches was important: should an investor switch styles and buy a value or growth share too soon, he/she may have to endure an extended period of under-performance.

Bartens and Hassan (2010), using a method that simulated investors only having prior information to choose predictor variables, tested whether size, value and momentum styles could be used to consistently outperform the market. They identified the best (and worst) trading strategies in-sample, and then applied these strategies out-of-sample, after which they rolled the in-sample window forward to identify a new set of trading rules, and so forth. Their results suggested that the equity styles are either ineffective or unstable over time, so in-sample predictability cannot be used to create profitable trading strategies in real time.

Muller and Ward (2012) found evidence to suggest that a trading strategy using a combination of equity styles could significantly and persistently outperform the market. They construct a combination equity style by starting with the best performing style, and systematically adding styles which contributed the

greatest improvement to the result. They found a combination style made up of momentum, return on capital, cash-flow to price and earnings yield to achieve the greatest results, consistently outperforming the market by about 14% per annum.

2.4.4 Hypothesis 3

H_0: The incorporation of P/E or B/M value measures into an optimised mean reversion trading strategy will not improve that strategy.

H_a: The incorporation of P/E or B/M value measures into an optimised mean reversion trading strategy will improve that strategy.

2.5 Conclusion of Literature Review

The literature review reveals that the JSE is probably weak-form efficient at best, so it may be possible to create a trading strategy that would be able to achieve market-beating returns. The evidence suggests that mean reversion and P/E and B/M value effects exist on the JSE, and that a savvy investor may be able to employ one, or a combination, of these phenomena to predict future earnings. However, as these effects may change over time, such an investor would be better served by using an optimisation approach than a trading rules with rigid parameters.

2.5.1 Hypothesis 1:

H_0: An optimised mean reversion trading strategy will not outperform the market.

H_a: An optimised mean reversion trading strategy will outperform the market.

2.5.2 Hypothesis 2:

H_0: An optimised value strategy that exploits the P/E effect or the B/M effect will not outperform the market.

H_a: An optimised value strategy that exploits the P/E effect or the B/M effect will outperform the market

2.5.3 Hypothesis 3:

H_0: The incorporation of P/E or B/M value measures into an optimised mean reversion trading strategy will not improve that strategy.

H_a: The incorporation of P/E or B/M value measures into an optimised mean reversion trading strategy will improve that strategy

CHAPTER 3: RESEARCH METHODOLOGY

3.1 Introduction

This chapter outlines the methodology that was used to conduct this research. To begin with, the data employed in this study and the procedure for data collection are described. An explanation of the research design follows, in which the complex computer simulation employed in this study and the methods by which its outputs were visually and statistically analysed are detailed. Limitations of the study are then discussed. The chapter concludes with a discussion on the validity and reliability of this study.

3.2 Data and data sources

3.2.1 Population and sample

The population for the research is all pure equity shares listed on the JSE.

The sample comprised normal shares of the top 200 companies by market capitalisation listed on the JSE as at 31 October 2012. There were no limitations to any particular sector. In order to create a more realistic scenario, shares that listed on the JSE after 1 November 2000 were included in the data set (provided they met the market capitalisation criterion as at 31 October 2012); this approach was considered preferable to simply excluding shares with incomplete time-series data, as it meant that the set of shares in the sample more closely matched the set that an investor would have had to choose from at the time.

3.2.2 Procedure for data collection

The data set covered the 12 years from 1 November 2000 to 31 October 2012.

The following daily data were downloaded from McGregor BFA:

- Market capitalisation
- Closing share prices
- Dividend payouts
- P/E ratios
- Number of shares issued (used to identify and resolve data anomalies)

Daily market-to-book ratios were downloaded from Bloomberg, as they were not available from McGregor BFA. SENS data and each company's ICB industry classification were downloaded from ShareData Online (www.sharedata.co.za).

The data relating to market capitalisation and number of shares were used to assist in the identification and resolution of data anomalies. Market capitalisation was also used to identify the top 200 shares that were ultimately included in the sample. SENS data was used to identify corporate actions. All other data were inputs into the optimisation models.

All time-series data was plotted on a set of charts, and the data was visually inspected for anomalies, one share at a time. For the most part, the data had already been adjusted for corporate actions, so no further action was necessary. The two most common exceptions were as follows:

- Where companies unbundled shares during the sample period, the data was adjusted to effectively "re-bundle" the shares, so that the returns calculated by the optimisation model matched those that would have been earned by an investor holding the shares over the unbundling period.
- McGregor BFA and Bloomberg had already backward adjusted the data for share splits and consolidations, however, it often happened that the value metrics had not been backward adjusted from the correct date. The result

was a few data points bordering the split or consolidation date that were obviously incorrect. These spurious data points were corrected.

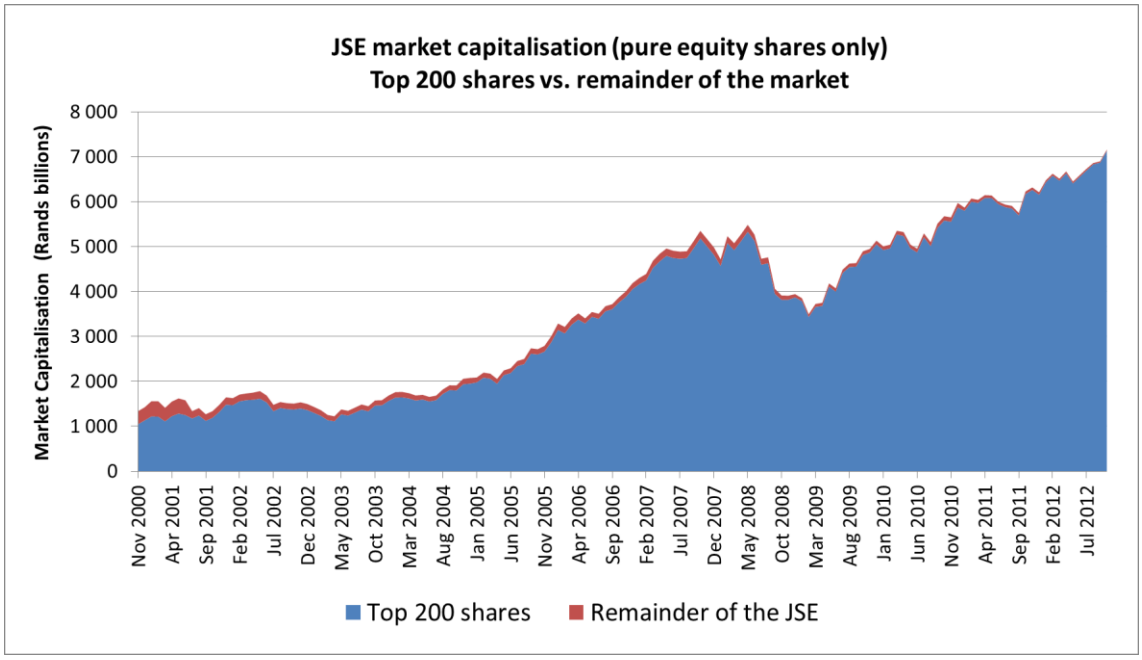


Figure 3: Market capitalisation of the top 200 shares on the JSE

As can be seen in Figure 3, in term of market capitalisation the top 200 shares on the JSE account for almost the entire market over the sample period (99.6% as at 31 October 2012).

3.3 Research design

Consider two extreme portfolios: a winner portfolio comprising the top performing shares measured over the immediately preceding formation period, and a loser portfolio comprising the worst performing shares over the same period. (Performance is measured either in terms of share price or some value metric). The portfolios are held for certain independent holding periods before being sold. The resulting sale prices determine the performance of both portfolios over the holding period. Each portfolio is optimised in terms of formation period, holding period and the number of shares in that portfolio. The performance of each portfolio is benchmarked against the entire population of the data set.

Based on the above scenario, it is proposed that:

i. The optimised winner portfolio will outperform the market, and

ii. The optimised loser portfolio will outperform the optimised winner portfolio.

The above approach is appropriate for this study as it has been shown in prior research that only through optimisation does it becomes possible to create portfolios that realise market-beating returns. O'Shaughnessy (1998) did not outperform the market when he performed a similar exercise, keeping both the formation and holding period fixed at one year. It was only when De Bondt and Thaler (1987) allowed the model to optimise itself and converge on optimal periods that excess returns were earned.

A further advantage of this approach is that the findings can easily be used to create a real-life, market-beating trading strategy, and that this can be done without an understanding of the factors that cause the arbitrage opportunity.

By testing both winner and loser portfolios, we increase the chances of this research being successful in identifying at least one trading strategy that generates market-beating returns.

3.3.1 The research instrument

This research took the form of a complex computer simulation, very similar to that used by Muller (1999). Portfolio returns were optimised in terms of eight dimensions:

- Winner or loser strategy (Winner : Loser)
- Starting date: (30 random dates)
- Formation period: (42 periods in steps of 35 days)
- Number of shares in the portfolio: (5 to 200 in steps of 5 shares)
- Holding period: (42 periods in steps of 35 days)
- Value measures: (P/E ratio and B/M ratio, with and without industry scaling)
- Value measure cut-off: (bottom quartile, median or upper quartile)
- Portfolio return: (the dependant variable)

The availability of large amounts of relevant quantitative data in the form of historical share prices and financial statistics, together with the relatively recent availability of affordable computing power, meant that it was possible, using this approach, to test literally millions of hypotheses in order to identify the optimal trading strategy. The flip side of the coin and a key disadvantage of the instrument is that it was subject to data-snooping bias.

3.3.2 Test portfolio generation

A series of MS Excel computer models were developed to calculate the return of a simulated portfolio for a given start date, formation period, number shares and holding period.

- The “start date” refers to the date in the test period on which shares are purchased to create the simulated portfolio.
- The “formation period” refers to the time before the start date, over which all shares are ranked in terms of price performance.
- The “holding period” refers to the period of time that the portfolio of shares is held before the shares were sold.

The 12-year test period was divided into three four-year intervals. The start date for the simulated portfolios varied randomly within 30 equally spaced periods in the middle third of the available time series (i.e. 1 November 2004 to 31 October 2008). The latin-hypercube sampling method was used to generate the 30 start dates, in order to avoid any issues that may have arisen through the formation of portfolios at the same time as each other or at the same time of the year (Iman, Campbell, & Helton, 1981). Once selected, the start dates were held constant for all simulations. The list of start dates may be found in Appendix A.

Two extreme portfolios were created for each pair of trading strategies tested: a winner or growth portfolio, comprising the top performing shares (by some measure) over the formation period immediately preceding the start date, and a loser or value portfolio, comprising the worst performing shares (by the same measure) over the same period. The shares in each portfolio were purchased

on an equal value weighted basis; in other words the initial holding of each share was the same in value terms.

The optimisation process entailed allowing the formation and holding periods to vary from 25 days to 4 years in steps of 35 days. Examples of the resulting portfolios are illustrated in Figure 4.

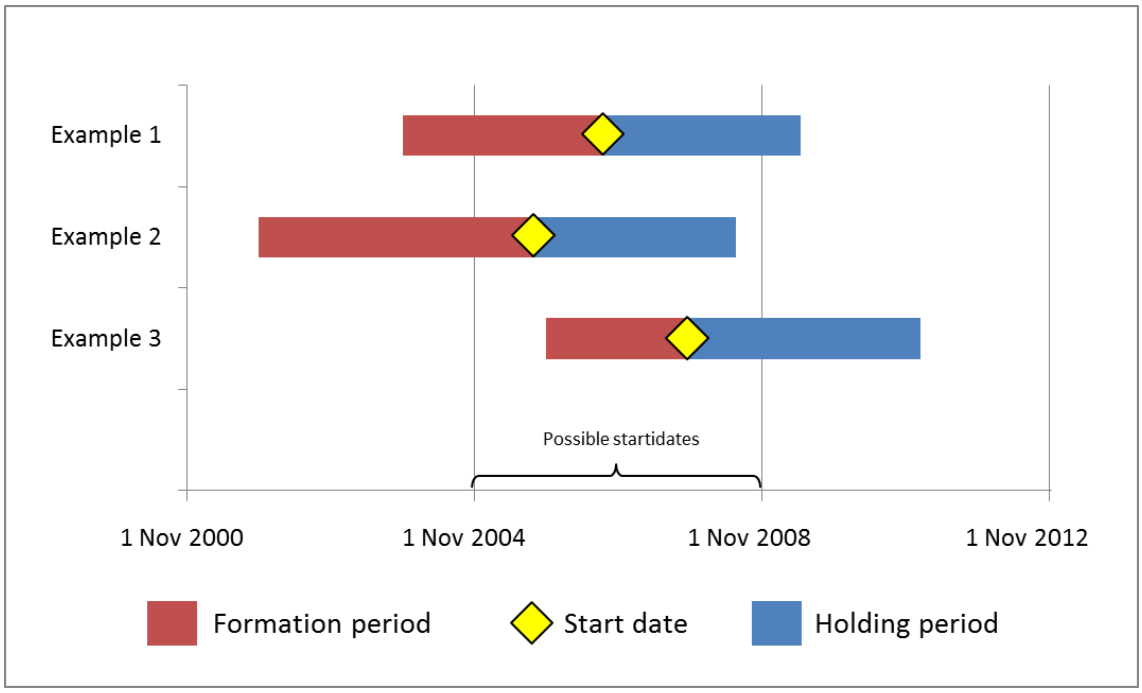


Figure 4: Examples of test portfolios created in the optimisation process by varying the start dates, formation periods and holding periods

Furthermore, the number of shares in each portfolio was allowed to vary from 5 to 200 in steps of 5 shares.

For each combination of start date, formation period, holding period and portfolio size, a portfolio return was calculated. The market return was also calculated, using the same start date, formation period and holding period, but holding the portfolio size at 200. The two resulting growth factors (i.e. the portfolio growth factor and the relevant market growth factor) were then divided to calculate the excess return against the market average, which was then annualised. Lastly, for each combination of start date, formation period and holding period, the excess returns relating to the 30 test portfolios (one for each of the 30 start dates) were averaged.

It is important to note that De Bondt and Thaler (1987) were severely criticised by Ball and Kothari (1989) when they used arithmetic methods to calculate expected returns in their empirical tests. Therefore, in order to avoid making the same mistake, all average returns were calculated as geometric means, and all annualised returns were calculated as geometric average rates of return. (This criticism is also the reason why excess returns were calculated by dividing growth factors, and not merely by subtracting nominal percentage outperformance).

It is also important to note that, because dividend receipts make a significant contribution to returns that an investor would receive, dividend payouts were added to capital appreciation over the holding period to calculate total portfolio and market returns.

Companies that listed on the JSE after 1 November 2000 were only considered for inclusion in the winner and loser portfolios and the market return calculation once they been listed for a minimum of six months (i.e. the beginning of the formation period was at least six months after the JSE listing date). The purpose of the six-month period was to allow the share prices and value measures to stabilise after the listing, so that the higher volatility associated with these companies immediately after listing did not distort the results.

In total, more than 2.5 million portfolios were simulated. The approximate time taken to calculate these portfolios' returns using an Intel i7 personal computer was 160 hours. By way of comparison, Muller (1999) ran 78,150 simulations.

3.3.3 Optimising the mean reversion strategy portfolios

Share prices growth was ranked over the formation period. Shares with the highest growth were included in the winner portfolio, and shares with the lowest growth were included in the loser portfolio.

In the initial simulations the size of the portfolios was kept at either 30 or 60 shares as the formation and holding periods were varied. Once optimal values for the formation and holding periods were determined for both winner and loser strategies, the restriction on portfolio size was lifted; the formation and holding periods were fixed, and the portfolio size was varied.

3.3.4 Optimising the value and growth investing strategy portfolios

As explained in section 1.5 (delimitations of the study), even though Hypothesis 2 refers specifically to value strategies, P/E and B/M growth strategies were also tested in this research. This was done because, for the purpose of this research, a value strategy was considered the equivalent of a mean reversion loser strategy, and a growth strategy was considered the equivalent of a mean reversion winner strategy. This meant that performing the growth strategy simulations was necessary in order to interpret the results of the combined strategy simulations (i.e. Hypothesis 3).

Formation periods did not apply to the value investing strategies. Instead, shares were ranked based on the value of their P/E and B/M ratios on the start date (i.e. the portfolio formation date):

- For P/E strategies, the shares with the highest P/E values were included in the growth portfolio, and the shares with the lowest P/E values were included in the value portfolio.
- For B/M strategies, the shares with the lowest B/M values were included in the growth portfolio, and the shares with the highest B/M values were included in the value portfolio.

As there were fewer variables in the value and growth models (without the formation period), it was not necessary to hold the share size constant. Instead,

both the portfolio size and holding periods were varied, completing the optimisation process in one step.

As investors tend to compare P/E and B/M shares ratios to those of similar companies (as opposed to the market at large), the process was repeated with the addition of industry scaling, to establish whether doing so improved the simulated returns. This entailed transforming each P/E and B/M ratio using the following formula:

$$\frac{\quad}{\quad}$$

Where:

- is the company in question's value metric (P/E or B/M ratio),
- is the median value metric of the set of all companies operating in the same industry, and
- is the industry scaled value metric.

The industry scaled value metrics were then ranked and used to create growth and value portfolios (using the same criteria as were used with the raw P/E and B/M ratios previously), and the optimisation process was repeated.

3.3.5 Optimising the combined strategy portfolios

The final set of simulations once again entailed using historical share performance to create winner and loser portfolios. The difference was that in this case, prior to the creation of winner and loser portfolios, shares were ranked by their P/E or B/M values as at the portfolio formation date, and shares with the highest or lowest P/E or B/M values were excluded from the sample set.

The creation of the combined strategies required that mean reversion strategies be combined with their equivalent P/E and B/M strategies: winner mean reversion strategies were combined with growth P/E and B/M strategies, and loser mean reversion strategies were combined with value P/E and B/M strategies. These combinations are described in Table 1 below.

Table 1: Combined trading strategy rules

	Winner/growth strategy	Loser/value strategy
P/E criterion	Shares with the largest P/E values were eligible for inclusion in the test portfolio	Shares with the smallest P/E values were eligible for inclusion in the test portfolio
B/M criterion	Shares with the smallest B/M values were eligible for inclusion in the test portfolio	Shares with the largest B/M values were eligible for inclusion in the test portfolio

In each case three P/E or B/M thresholds were tested:

- A 75% threshold (i.e. = after the P/E or B/M ranking, 75% of the original shares were eligible for inclusion in the test portfolio);
- A 50% threshold (i.e. = after the P/E or B/M ranking, 50% of the original shares were eligible for inclusion in the test portfolio), and
- A 25% threshold (i.e. = after the P/E or B/M ranking, only 25% of the original shares were eligible for inclusion in the test portfolio).

In total 12 strategies were tested (4 combinations x 3 thresholds).

Where industry scaling had been shown to improve the results generated by the P/E and B/M strategies, such scaling was employed in the combined strategies.

3.3.6 Graphical representation of the results

The results of the above simulations are initially presented as three-dimensional surface charts. For the mean reversion and combined strategies, the x, y and z-axes relate to the formation period, the average excess returns (across all 30 start dates), and the holding period respectively. For the value and growth

strategies, the x-axis related to the portfolio size instead of the formation period (because the formation period variable does not apply to these strategies).

In the case of mean reversion and combined strategies, once optimal holding and formation periods have been identified, the portfolios created by holding the formation and holding periods constant while allowing the number of shares to are then plotted on two-dimensional charts.

Charting the results in this manner allowed for the visual identification of optimal portfolio variables. When identifying optimal portfolio variables, smooth, well auto-correlated surfaces, where points of outperformance were supported by adjacent cells of similarly high return were preferred to spurious spikes in returns, as the former suggested reliable results that are not simply a consequence of outliers in the data.

It should be noted that, because of the decision to include incomplete time-series in the analyses, the effective maximum number of shares in any simulation was less than 200 (approximately 160 shares on average). This meant that from a certain portfolio size, increasing the number of shares in subsequent simulations resulted in identical portfolios, as the portfolio equalled the sample market. This did not affect the validity of the results, as the sample still accounted for almost all of the JSE's market capitalisation (refer to Figure 3), and for each formation date the same set of shares were used to calculate the portfolio and the market returns. It did, however, mean that as portfolio sizes were increased, excess returns reached zero sooner (i.e. at approximately 160 shares instead of 200 shares) than the reader may have expected. For the sake of comparison, the three-dimension surface charts relating to the growth and value strategies were not truncated to account for this fact – the maximum share price on these charts remains as 200 shares.

3.3.7 Statistical tests

Statistical tests will be used to assess the significance of the findings. In the cases of the mean reversion and combined strategies, each surface consisted of 42 by 42 grid, resulting in 1,764 data points. With the growth and value strategies, each surface consisted of a 42 by 40 grid, resulting in 1,680 data points. In each both cases the following statistical tests were performed:

a) Portfolio outperformance was first compared by using a two-tailed two-proportion z-test (pooled for H_0: $p_1 = p_2$) to test for differences in the proportions of positive excess returns across pairs of portfolios (i.e. the percentage of grid points on the plotted surface charts where the portfolio returns are greater than the market returns):

Differences in proportions of positive excess returns were tested across pairs of surfaces using a significance level of 5%. The critical *z*-value for α=5% was 1.96.

b) Pairs of surfaces were also tested for having different means using a two-tailed two-sample pooled t-test (with equal variances):

Once again all tests were conducted using a significance level of 5%. Because of the large sample sizes, the critical t-value for α = 5% was 1.96.

c) Lastly descriptive statistics, including 95% confidence intervals, were calculated for optimal portfolios.

Confidence intervals were used to compare portfolios where comparison of the portfolios' mean returns their standard deviations did not reveal a clear winner. For example, consider the following two hypothetical portfolios:

			95% Confidence Limits	
	Return (%)	Standard Deviation (%)	Lower (%)	Upper (%)
Portfolio A	18	32	7	30
Portfolio B	10	25	-3	18

The return generated by portfolio A is greater than that generated by portfolio B (18% vs. 10%), but A's standard deviation is also greater than B's (32% vs. 25%). A is likely to achieve a higher return but with higher risk, so one can't say that A is the better portfolio. However, because B's lower confidence limit is negative, an investor investing in portfolio B runs a much greater risk of realising a negative return than he would should he invest in portfolio A, where by definition 95% of all returns will be greater than or equal to 7%. Therefore, for the purposes of this research, portfolio A would be considered the better portfolio.

Given the nature of the research, there were several weaknesses in using the above statistical tests that needed to be considered when interpreting the results:

- It is possible to considerably change the surfaces without changing the proportion positive measure by, for example, multiplying every point on the surface by two; doing so will increase the magnitude of positive returns and decrease the magnitude of negative returns without changing the proportion of positive returns. Proportion tests do not speak to the magnitude of expected returns.

- Neither the difference-in-proportion nor the difference-in-mean tests are influenced by the smoothness or degree of auto-correlation of the surfaces. As explained previously, smooth surfaces are preferable to rough surfaces as they provide more confidence in the underlying trends that created those surfaces. Also, should the optimal portfolio variables change slightly, an investor can still expect to earn a return similar to that generated by the optimal portfolio if the surface is smooth.

- Difference-in-proportion tests have less meaning at proportions close to 0% and 100%. (However, as will be seen in the next section, most of the proportions in this study did not reach either of these extremes).

- Both the difference-in-proportion and difference-in-mean tests depend greatly on the arbitrarily chosen cut-offs and test cases. For example, it is possible that a ridge of high returns could be included in the surface for a portfolio size of *x* shares, but shifted horizontally off the surface for a portfolio size of *y* shares; in this example the shift of the ridge off the surface in the case of a *y*-share portfolio might not have happened had a different holding period cut-off been chosen (i.e. had the dimension of the surface under observation changed).

3.4 Limitations of the study

- The returns realised by the simulated portfolios (calculated as capital appreciation plus dividend payouts) were judged against the market average. No adjustments will be made to compensate for size, risk or any other risk factors that may have influenced returns.

- Annualising short-term returns could have distorted the results of this research. Therefore special attention was paid during the analysis to disregard short-term returns.

- Survivorship bias existed as companies that delisted from the stock exchange were not be eligible for inclusion in the sample. (Collecting data for delisted companies is a time-consuming and expensive process). The effect of the bias was lessened by the fact that the study only considered the top 200 shares in terms of market capitalisation, the reason being that larger shares are less likely to delist than smaller stocks.

- Liquidity of shares was not considered. Firstly, if shares are illiquid it may not be possible to use the results of this research to create a real-life trading strategy. Secondly, as shareholders consider liquidity to be a significant investment criterion, the results of this study may be skewed by the potential link between liquidity with higher returns. Again this limitation was lessened by the fact that the study only considered the top 200 shares in terms of market capitalisation, the reason this time being that the shares of large companies are generally more liquid than those of small companies. A further advantage of excluding the smallest companies is that any abnormal returns generated in this study are less likely to be caused by the size effect.

- Similarly, the potential to use the results of this research to create a real-life trading strategy could be limited by transaction costs, such as brokerage fees and taxes; these costs were not accounted for in the study. This limitation was mitigated by the fact that, all things being equal, the portfolios with longer holding periods were preferred to those with shorter holding

periods, as transaction costs are not material over long holding periods (i.e. holding periods in the order of years).

- Evidence of in-sample predictability discovered in a study such as this one does not guarantee predictability which can be exploited in real time. Lo and MacKinlay (1990) find that the effects of data snooping can be substantial in tests based on returns to portfolios of common stock, where portfolios are constructed on some empirically motivated characteristic. The predictive value may also be limited by unstable relationships between cross-sectional excess returns and independent variables (Bossaerts & Fohlin, 2000).

  The design of this research and method in which the results were analysed limited the risk of data snooping. For example, returns realised by simulated portfolios were charted as three-dimensional surfaces and then visually inspected, and in the process improbable spikes in returns were rejected, and returns well supported by adjacent cells were accepted.

- It is possible that the inclusion of the 2008 global financial crisis in the sample period may lessen the predictive value of a historical analysis such as this one. Market fundamentals and investor behaviour may have changed significantly as a result of the turbulent investment environment.

3.5 Validity and reliability

The validity and reliability of a measurement instrument influence the degree to which one can draw insights from the phenomenon that is being studied, the probability that findings assembled through data analysis will be statistically significant, and the extent to which one can draw meaningful conclusions from the data (Leedy & Ormrod, 2001).

Validity refers to how well a scientific test or piece of research actually measures what it sets out to, or how well it reflects the reality it claims to represent. Reliability, on the other hand, speaks to the consistency of the research results over time, and whether the results of the study can be accepted as an accurate representation of the total population under study (Golafshani, 2003).

3.8.1 External validity

External validity, in the context of this research, is the confidence in generalising results and findings of this research across markets and times not included in the study (Johnson, 1997).

Momentum and value effects present investors with arbitrage opportunities, and arbitrage opportunities by definition tend to disappear as investors recognise them and find ways to exploit them. That said, even though the exact nature and intensity of the effects seems to change over time, prior research has generally found momentum and value effects to be persistent over time. Therefore, any effective trading strategies identified through this research are not expected to be valid for any extended period of time (i.e. more than a few years), though this period of validity might be extended if the optimal parameters are routinely recalculated to accommodate for changes in the effects over time.

This research limits itself to pure equity shares listed on the JSE and does not make claims about other markets or types of securities. When looking at contrarian strategies across international markets, prior research has been able

to draw parallels across similar markets, but has ultimately found these strategies not to be successful in every country or every year (Bauman, et al., 1999). Viewed in isolation, this research would not be valid across other markets, however, it can be argued that similar markets may derive value from this study when its results are considered in conjunction with the other literature.

That validity of this research is maximised through the inclusion of a large number of shares that collectively account for a large percentage of the JSE's market capitalisation. Furthermore, should an institutional investor put together a fund to exploit the results of this study, from a practical point of view it makes more sense to only consider the shares of bigger companies with larger market capitalisation.

3.8.2 Internal validity

Internal validity refers to the relationship between dependant and independent variables in the research: it addresses whether or not an observed covariance should be interpreted as a causal relationship (Calder, Phillips, & Tybout, 1982). It follows that internal validity is only relevant when attempting to establish a causal relationship between two or more variables.

The focus of this study is the identification of profitable trading strategies, not the investigation of potentially causal relationships between share returns (the dependant variable) and past share prices and/or value measures (the independent variables), so internal validity as defined by Calder, et al. (1982) is not relevant to this research. It may, for example, be the case that the correlation between the dependant and independent variables is the result of a third unknown variable causing both changes in the value measures and subsequent changes in shares returns; though the identification of this causality would definitely be interesting and probably facilitate the development of further trading strategies, it is not required for any trading strategies identified in this research to be useful.

3.8.3 Reliability

Reliability in the context of this research refers to consistency which the research tool yields a certain result when the object being measured hasn't changed (Leedy & Ormrod, 2001).

In terms of the data employed in this study, it is assumed that the data sets employed were correct. As the data came from reputable sources, and as they are used by many people, one can safely assume that any significant errors would have been detected and rectified. Furthermore, it is assumed that any changes in accounting standards over the study period did not have a significant effect on the calculated values of the P/E and B/M value measures. That said, all time-series data was inspected and exception tested to ensure that no errors were made by the researcher when downloading the data, and that the data had been correctly adjusted for all corporate actions (such as share splits).

In terms of facilitating repeatability of this study, all methodology, data manipulations and randomly chosen portfolio start dates, formation periods and holding periods have been thoroughly documented.

CHAPTER 4: PRESENTATION OF RESULTS

4.1 Introduction

The empirical results of this study are presented in this chapter. Each hypothesis is tested in a separate section:

Section 4.2 presents the performance of test portfolios generated using winner and loser mean reversion trading strategies. The questions that the section attempts to answer are firstly, whether the two strategies could be used to generate excess returns, and secondly, whether the loser strategy outperforms the winner strategy.

Section 4.3 presents the performance of P/E and B/M growth and value strategies, and attempts to establish whether each of these strategies could be used to generated excess returns. Each trading strategy is tested both with and without industry scaling to establish whether scaling each share's value metric by its industry's median value improves that strategy.

Section 4.4 presents the performance of trading strategies that incorporate value measure restrictions into mean reversion trading strategies. This section attempts to establish whether these combined trading strategies outperform strategies based on either mean reversion or value investing exclusively.

Each section initially presents the results of the test portfolios visually, and concludes with a statistical comparison of the average excess returns generated by the test portfolios for each of the trading strategies and sets of optimal portfolio parameters.

4.2 Results pertaining to Hypothesis 1

4.2.1 Winner strategy

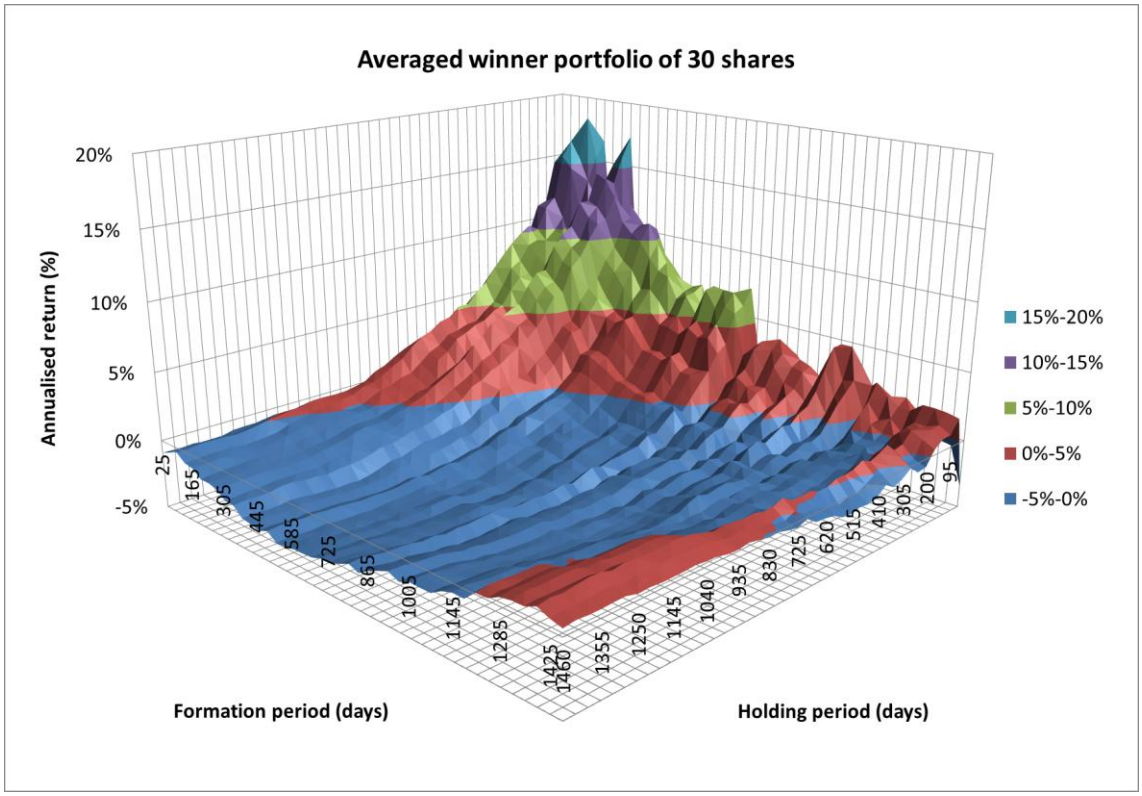


Figure 5: Excess returns generated by 30-share winner strategy

A winner strategy with portfolio size held constant at 30 shares (Figure 5) created a reasonably smooth and auto-correlated surface of excess returns. Average excess returns peaked significantly for short holding and formation periods, and decreased rapidly as either of these periods increased, quickly falling to negative values and only becoming marginally positive again for the several longest formation periods. A maximum average excess return of 18.5% was achieved with a formation period of 165 days and a holding period of 60 days.

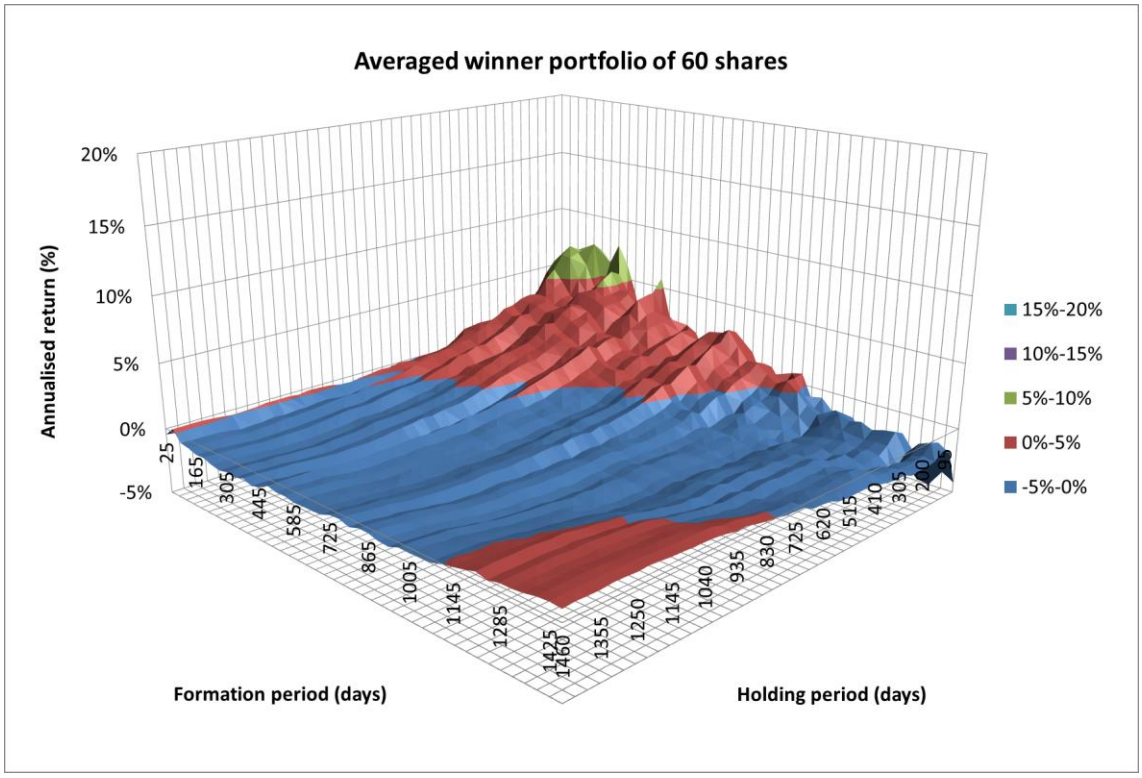


Figure 6: Excess returns generated by 60-share winner strategy

Increasing the portfolio size to 60 shares (Figure 6) had the effect of flattening out and smoothing the surface while maintaining the same general shape. A maximum average excess return of 7.8% was achieved with a formation period of 270 days and a holding period of 25 days. Excess returns remained positive for shorter holding and formation periods (i.e. closer to the peak) than was the case with a portfolio of 30 shares. The area of positive excess returns at high formation and holding periods increased marginally in size.

In order to the see the effect of portfolio size *ceteris paribus*, three sets of formation periods and holding periods were tested (expressed below as "formation period - holding period"):

- 165-60 (highest return for 30-share portfolio)
- 270-25 (highest return for 60-share portfolio)
- 130-95 (second highest return for both 30 and 60-share portfolios)

The results are depicted in Figure 7 below.

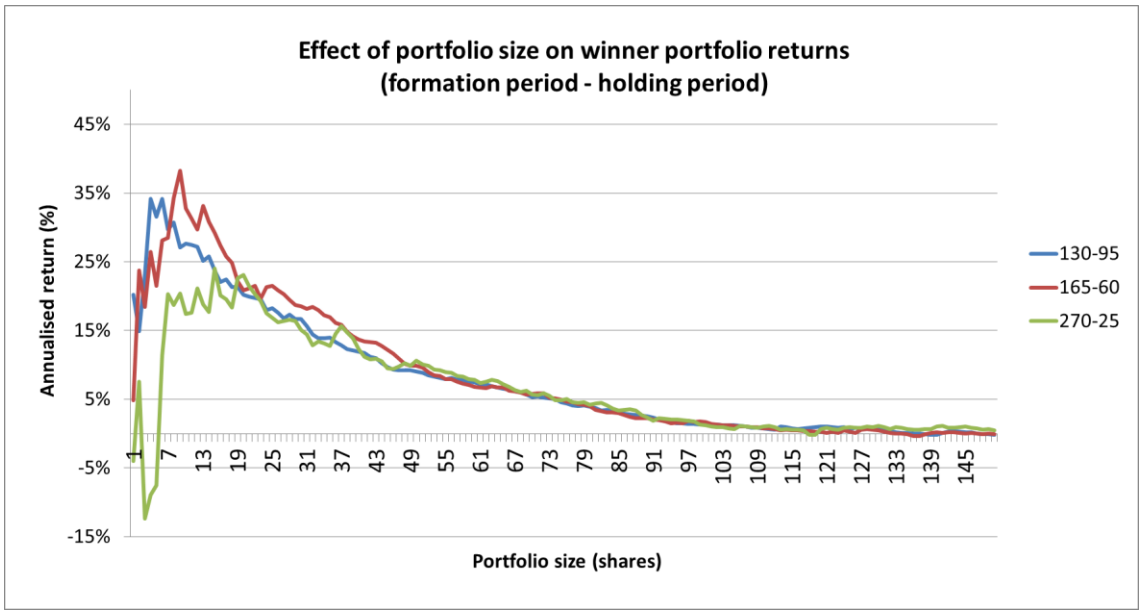


Figure 7: Effect of portfolio size on winner portfolio returns

As expected, after an initial peak the excess market return decreased to zero as the number of shares increased, until with approximately 115 shares the portfolio effectively mirrored the market (as proxied in this study). Returns were largest but highly erratic for small portfolio sizes, seeming to stabilise for portfolios greater than approximately 20 shares and converge for portfolios of more than approximately 50 shares.

4.2.2 Loser strategy

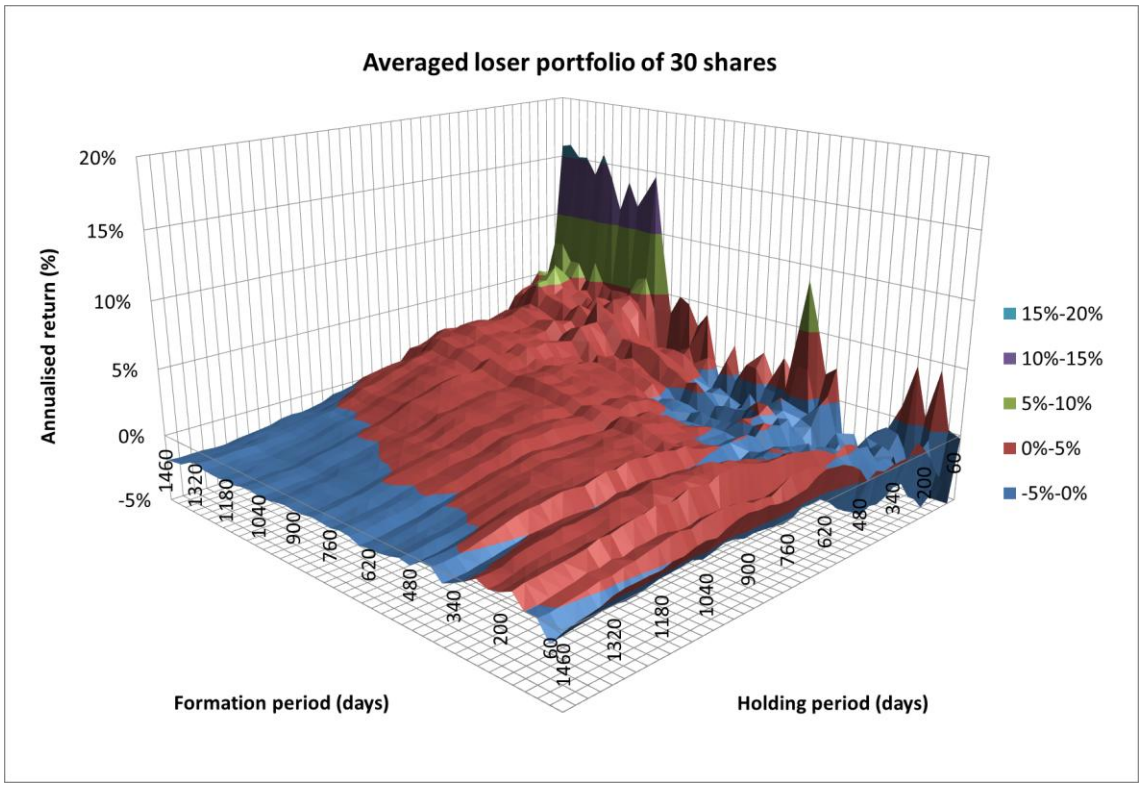


Figure 8: Excess returns generated by 30-share loser strategy

With the exception of low holding periods, a loser strategy with portfolio size held constant at 30 shares (Figure 8) created a relatively flat surface, with corrugations that became less pronounced for larger formation periods. Returns peaked significantly for long formation periods and short holding periods, and decreased rapidly as the holding period was increased. For holding periods less than 270 days and formation periods less than 1,000 days, the surface exhibited erratic spikes in excess returns. A bridge of relatively small positive returns (less than 3.7%) ran diagonally across the surface, seeming to peak approximately where the sum of the formation period and the holding period equalled 1,500. A maximum average excess return of 16.1% was achieved with a formation period of 1,425 days and a holding period of 25 days.

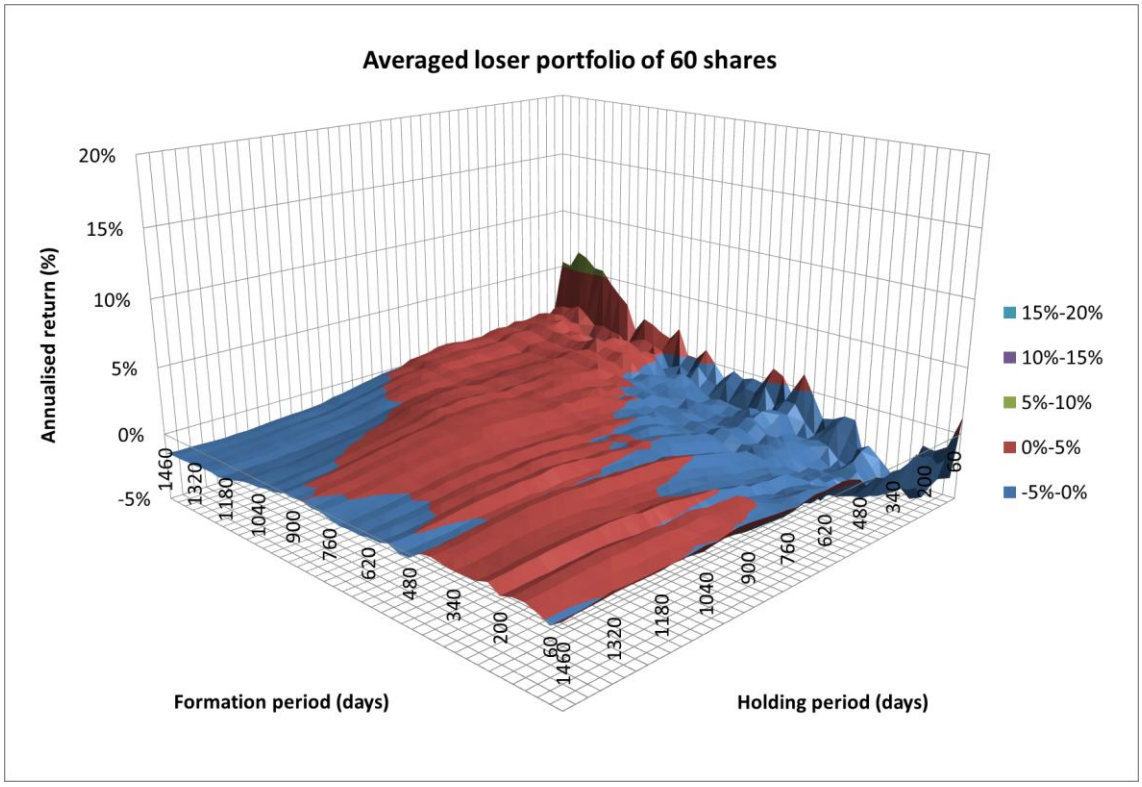


Figure 9: Excess returns generated by 60-share loser strategy

As was the case with the winner portfolio, increasing the portfolio size to 60 shares (Figure 9) had the effect of flattening out and smoothing the surface while maintaining the same general shape. The erratic positive peaks previously experienced for holding periods less than 270 days and formation periods less than 1,000 days had virtually disappeared. The bridge of slightly positive returns was still apparent, but had shifted towards longer holding periods. A maximum average excess return of 6.6% was achieved with a formation period of 1,390 days and a holding period of 25 days.

In order to the see the effect of portfolio size *ceteris paribus*, three sets of formation periods and holding periods were tested (expressed below as "formation period - holding period"):

- 1,425-25 (highest return for 30-share portfolio)
- 1,425-60 (highest return for 30-share portfolio with holding period greater than 25 days)
- 1,355-60 (highest return for 60-share portfolio with holding period greater than 25 days)

The results are depicted in Figure 10 below.

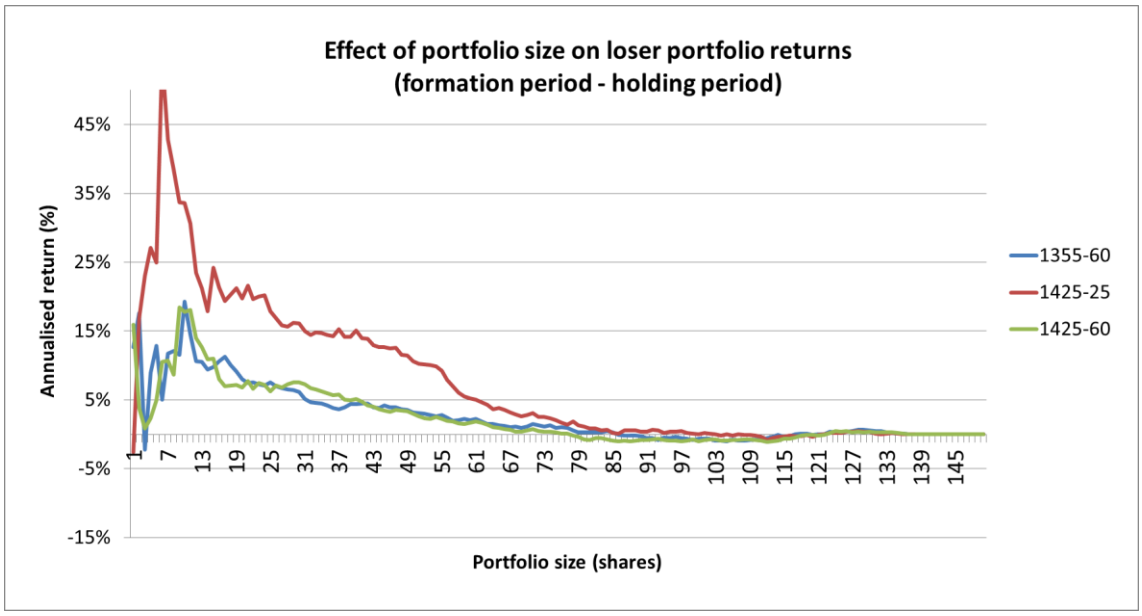


Figure 10: Effect of portfolio size on loser portfolio returns

After peaking briefly with a portfolio size of 6 shares, the returns generated by the 1,425-25 set of portfolios decreased rapidly as the number of shares increased to 15. For almost all portfolio sizes the excess returns generated by the 1,425-25 set of portfolios were approximately double those generated by the other two sets of portfolios; this observation is consistent with the idea that the greatest excess returns were earned in the first 25 days, and the longer holding period only served to dilute the average returns. In all three cases portfolios of greater than 80 shares generated returns that approximated market returns.

4.2.3 Statistical tests

Table 2: Proportion positive of each mean reversion strategy surface and significant differences

	30 Shares	60 Shares	z	Result
Winner Strategy	36.7%	31.9%	3.01	Different
Loser Strategy	65.2%	54.9%	6.26	Different
z	16.91	13.76		
Result	Different	Different		

Table 2 lists the results of a set of two-tailed proportion tests that were performed on the surfaces at a significance level of 5%. (Reading horizontally holds the strategy constant, while reading vertically holds the portfolio size constant). The proportion of positive excess returns was much larger for the loser surfaces than for the winner surfaces. For both winner and loser strategies, increasing the portfolio size resulted in a decrease in the proportion of positive earnings. The extremely high *z*-values evidenced the very clear differences between winner and loser strategies. The differences between portfolios of size 30 and 60 shares were less pronounced, but still statistically significant.

Table 3: Mean excess returns of each mean reversion strategy surface and significant differences

	30 Shares	60 Shares	t	Result
Winner Strategy	Mean = 0.18% Std dev = 3.58%	Mean = -0.26% Std dev = 1.63%	4.72	Different
Loser Strategy	Mean = 0.76% Std dev = 2.01%	Mean = -0.18% Std dev = 1.29%	16.46	Different
t	5.91	1.69		
Result	Different	Not different		

Table 3 lists the results of a set of two-tailed *t*-tests for equal means that were performed. The tests revealed significant differences at a significance level of 5% for all surfaces except the winner and loser 60-share surfaces. As one would expect, for both winner and loser strategies, standard deviations of excess returns for the 30-share portfolios were greater than standard deviations for the 60-share portfolios, as the 30-share portfolios were less diversified.

Table 4: Distribution of sample returns at mean reversion strategy surface peaks

						95% Confidence Limits	
Surface	Size (shares)	Formation (days)	Holding (days)	Return (%)	Standard Deviation (%)	Lower (%)	Upper (%)
Winner Strategy	30	165	60	18.5	32.1	7.1	30.0
	60	270	25	7.8	26.3	-1.6	17.2
Loser strategy	30	1425	25	16.1	73.4	-10.2	42.3
	60	1390	25	6.6	33.2	-5.3	18.5

Table 4 details the location (in terms of portfolio size, formation period and holding period) of the point of maximum return on each surface, together with the associated standard deviation and 95% confidence limits. It is important to note that holding period returns and standard deviations have been annualised.

Based on the above confidence limits, an investor would find a winner strategy preferable to a loser strategy for both 30 and 60-share portfolios. With higher upper and lower confidence limits, a 30-share winner portfolio would clearly be preferable to a 60-share winner portfolio. The distinction between 30 and 60-share loser portfolios is less clear, with an investor needing to choose between lower volatility or higher returns.

Table 5: Distribution of sample returns at points of maximum stable return on mean reversion strategy surfaces

Surface	Size (shares)	Formation (days)	Holding (days)	Return (%)	Standard Deviation (%)	95% Confidence Limits	
						Lower (%)	Upper (%)
Winner Strategy	30	165	60	18.5	32.1	7.1	30.0
	60	200	60	7.7	15.3	2.2	13.2
Loser strategy	30	1355	165	6.3	20.0	-0.9	13.4
	60	1355	60	2.1	21.2	-5.5	9.7

Table 5 also describes the distribution of the points of maximum return on each of the surfaces, but in this case, points of high return that were not surrounded by adjacent cells of similarly high returns were disregarded.

Disregarding points that were not surrounded by points of similarly high returns did not change the 30-share point of maximum return, because even though the maximum was located at the tip of a pinnacle with steep sides, the surrounding surface was smooth. It is interesting to note that, while the point of maximum return for the 60-share winner portfolio dropped marginally from 7.8% to 7.7%, its confidence interval almost halved in width.

As one would expect after seeing the surface charts, the points of maximum return dropped considerably for both loser surfaces. The new points of maximum return were associated with narrower confidence intervals, however, the lower limits remained negative (-0.9% for the 30-share surface and -5.5% for the 60-share surface).

4.2.4 Hypothesis 1 conclusion

The hypothesis tested in this section was as follows:

H_0: An optimised mean reversion trading strategy will not outperform the market.

H_a: An optimised mean reversion trading strategy will outperform the market.

For both the winner and the loser strategies, visual inspection of the resulting three-dimensional surfaces revealed large areas of positive excess returns. The statistical tests assisted in gaining an understanding of how changing the portfolio variables affected these excess returns.

The outputs from the above simulations would allow an investor to select a portfolio that would generate maximum returns while maintaining risk (in terms of share price volatility) at a palatable level. Therefore, assuming that past events are a predictor of future share price behaviour, we must reject the null hypothesis in favour of the alternate hypothesis, and conclude that an optimised mean reversion strategy will outperform the market.

4.3 Results pertaining to Hypothesis 2

In contrast to the mean reversion trading strategies, the formation period variable did not apply the value and growth trading strategies; instead of ranking shares by the returns that they generated over a formation period, shares were ranked based on the magnitude of their value metrics on the formation date. This simplified the optimisation process, and meant that it was practical to create three dimensional surfaces portraying average excess returns across portfolio sizes and holding periods (as opposed to plotting returns across formation periods and holding periods). It is important to note that the surfaces in this section are therefore not directly comparable to those depicted in section 4.2 above or section 4.4 below.

4.3.1 Price-to-earnings growth strategy

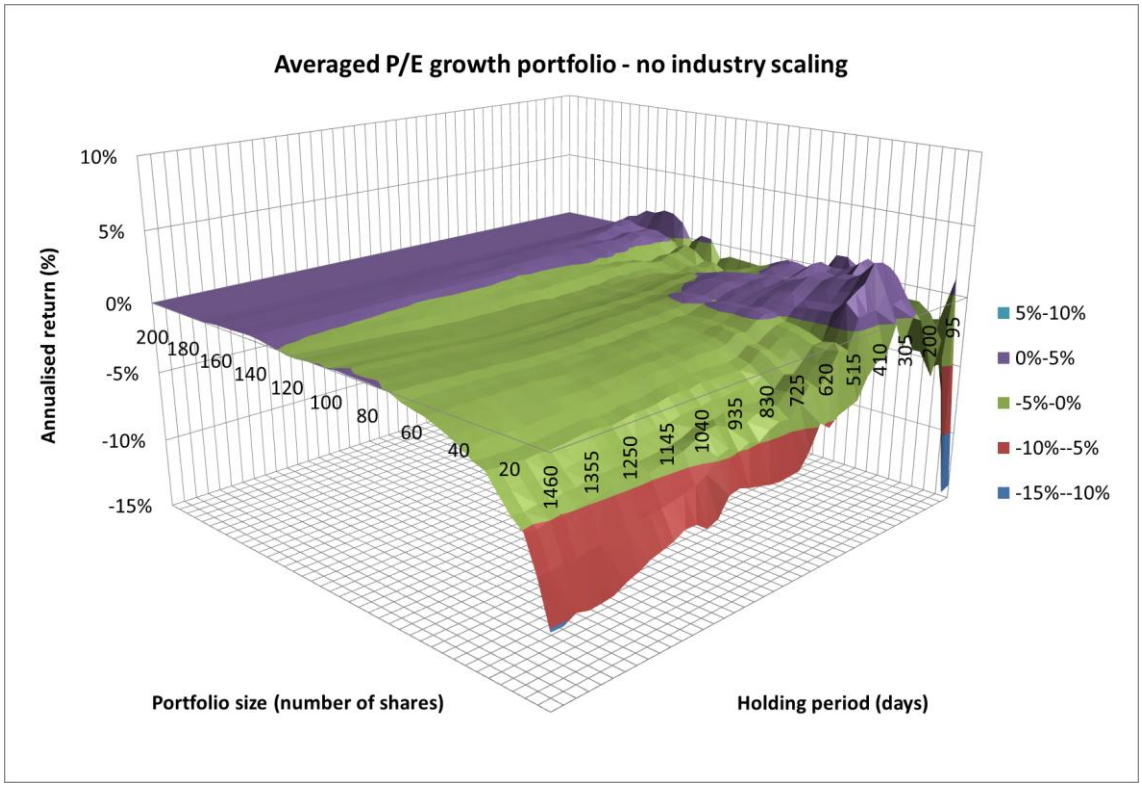


Figure 11: Excess returns generated by P/E growth strategy - no industry scaling

A P/E growth strategy without industry scaling (Figure 11) created a reasonably smooth and auto-correlated surface of excess returns. As expected, the surface flattened out as the portfolio size increased and average returns approached market returns. Average excess returns were negative over the majority of the surface; returns dipped sharply negative for portfolios smaller than 15 shares, and at no point did holding periods greater than 480 days exhibit positive average excess returns greater than 0.4%. A small area of positive excess returns existed for holding periods between 10 and 80 days, peaking at a value of 3.7% for a 15-share portfolio with a holding period of 340 days.

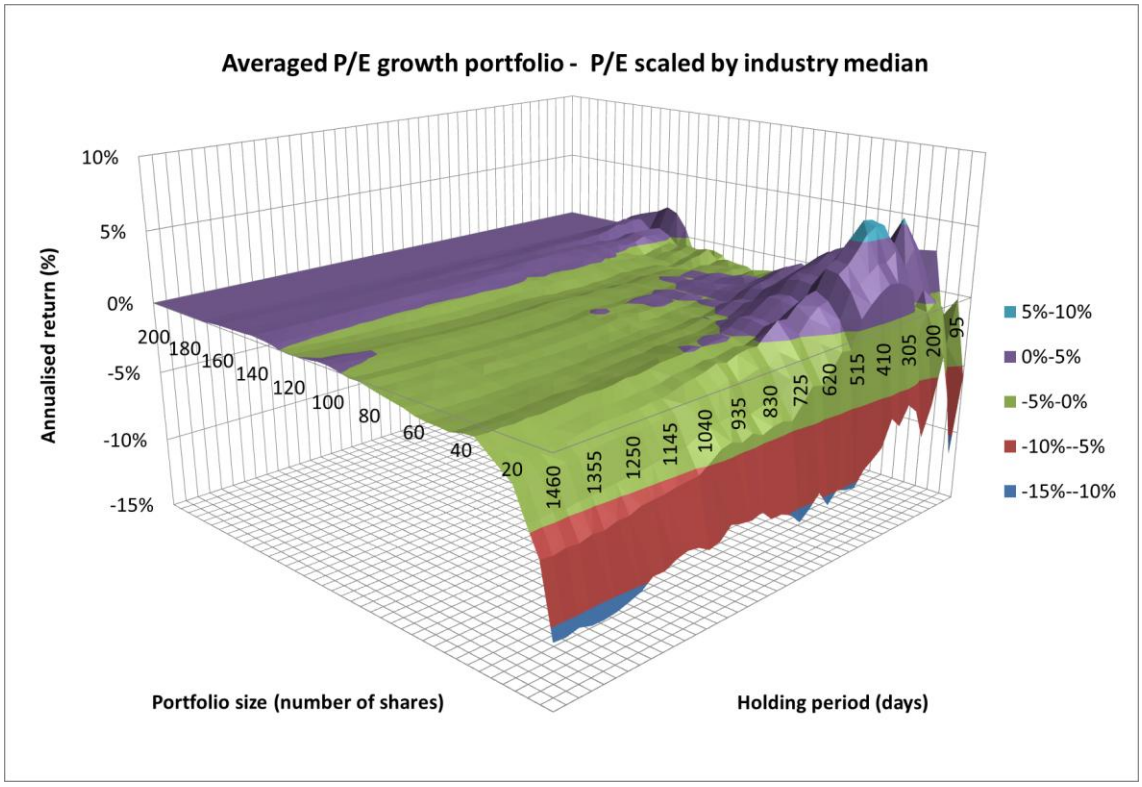


Figure 12: Excess returns generated by P/E growth strategy - P/E scaled by industry median

Adjusting the P/E growth strategy by scaling each P/E value by the share's industry median (Figure 12) had the effect of exaggerating the surface, making the peaks higher and the dips lower. The two areas of positive returns both increased in size, and a maximum average excess return of 6.1% was reached by a 25-share portfolio with a holding period of 305 days.

In order to facilitate comparison of the above 2 surfaces, cross-sections were charted for three promising portfolio sizes, namely 30, 40 and 50 shares.

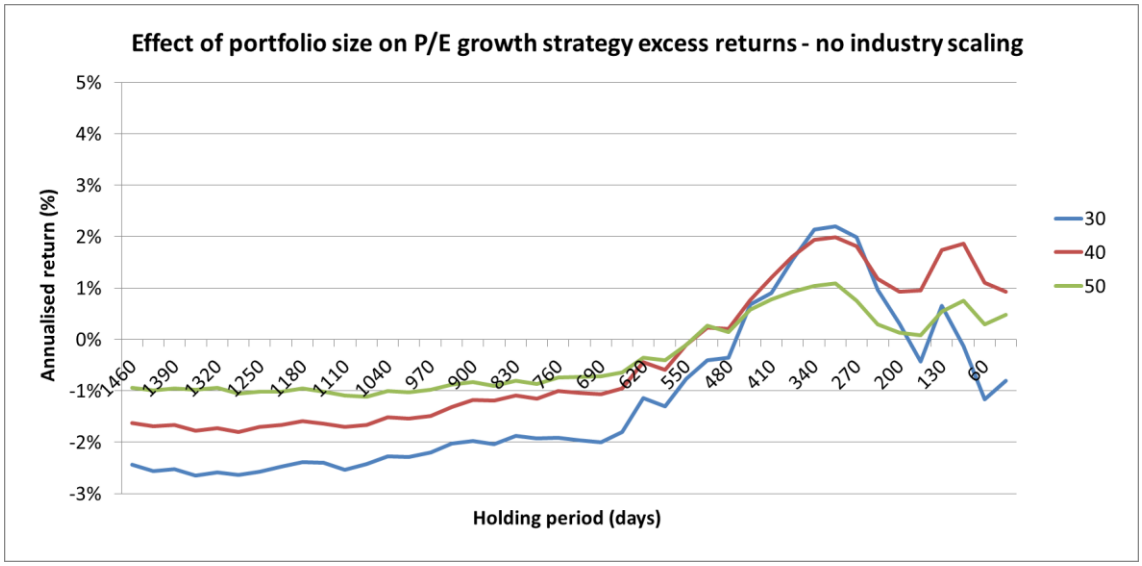


Figure 13: Effect of portfolio size on P/E growth strategy excess returns - no industry scaling

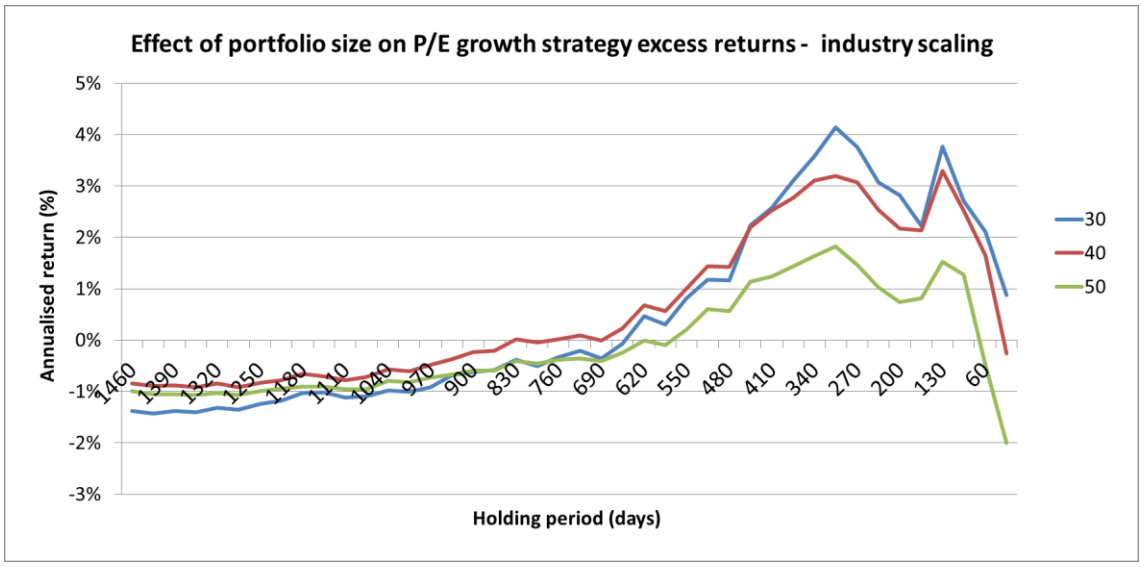


Figure 14: Effect of portfolio size on P/E growth strategy excess returns - P/E scaled by industry median

In comparing the resulting Figures 13 and 14, is it is clear that the inclusion of industry scaling in the P/E growth strategy improves the results noticeably for all three portfolio sizes: returns were positive over a greater set of holding periods,

and with the exception of holding periods of 25 and 60 days, returns were greater for all holding periods.

4.3.2 Price-to-earnings value strategy

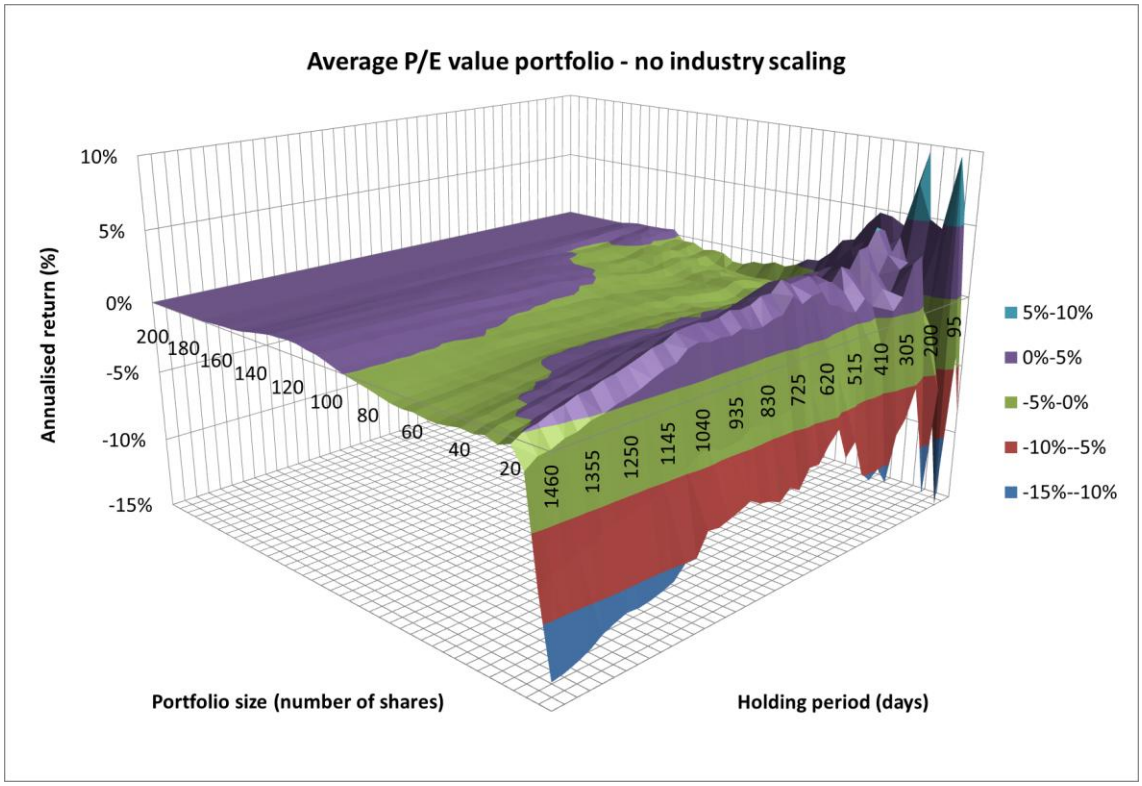


Figure 15: Excess returns generated by P/E value strategy - no industry scaling

The surface created by a P/E value strategy without industry scaling (Figure 15) shared several characteristics with the corresponding P/E growth surface: in both cases returns dipped sharply negative for portfolios smaller than 15 shares, and quickly plateaued after portfolios passed a certain threshold (approximately 70 shares for the growth strategy and approximately 50 shares for the value strategy). Ignoring the two pinnacles that occurred at holding periods of 25 and 60, which each appear to be the result of single outliers, the growth and value surfaces also shared similar peaks: the growth strategy excess returns reached 3.7% with a portfolio of 15 shares and a holding period of 340 days, while the value strategy excess returns reached a slightly larger 5.2% with a portfolio of 25 shares and a holding period of 235 days. The most noticeable difference between the two surfaces was that the area of meaningful

positive returns extended much further in the value portfolio, only disappearing at a maximum holding period of approximately 1,300 days.

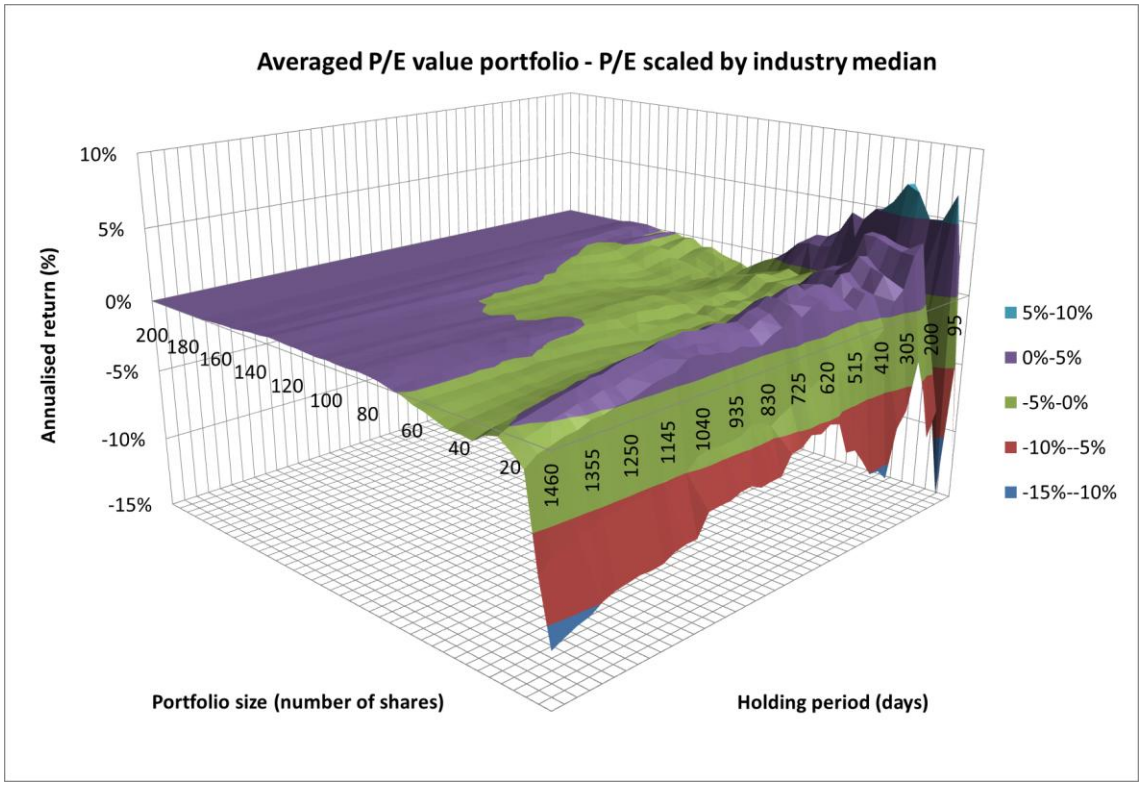


Figure 16: Excess returns generated by P/E value strategy - P/E scaled by industry median

Adjusting the P/E value strategy by scaling each P/E value by the share's industry median (Figure 16) made very little difference to the resulting surface. For the vast majority of the surface, returns were slightly lower than they were without industry scaling.

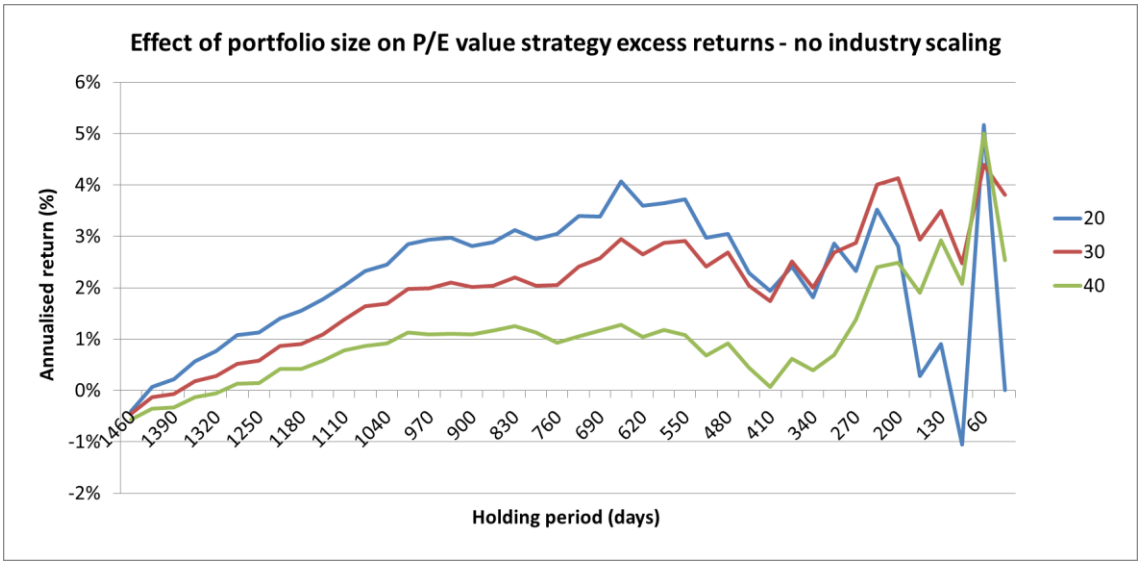


Figure 17: Effect of portfolio size on P/E value strategy excess returns - no industry scaling

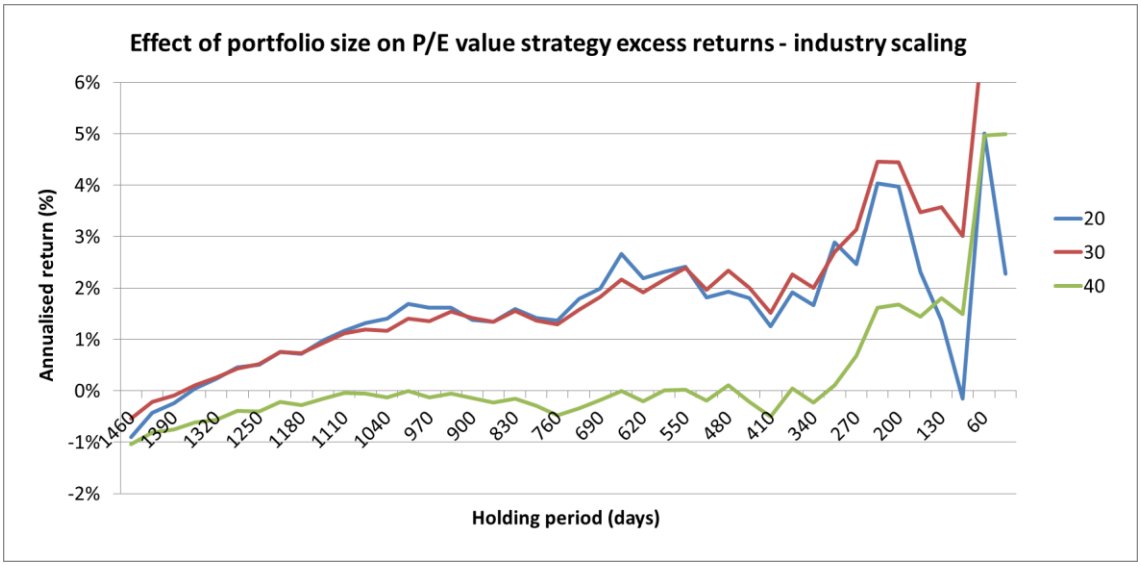


Figure 18: Effect of portfolio size on P/E value strategy excess returns - P/E scaled by industry median

The 20, 30 and 40-share cross-sections (Figures 17 and 18) confirmed first impressions gleaned from the surface charts. For all three portfolio sizes the addition of industry scaling did not noticeably change the returns generated for holding periods less than 410 days, however, for holding periods greater than 410 days, the addition of industry scaling visibly lowered the returns.

It was noted that in the case of a P/E value strategy without industry scaling, a 20-share portfolio generated excess returns of approximately 3% for all holding periods between 200 and 1,000 days.

4.3.3 Price-to-earnings strategy statistical tests

Table 6: Proportion positive of each P/E strategy surface and significant differences

	No Industry Scaling	Industry Scaling	z	Result
Growth Strategy	45.4%	50.1%	2.73	Different
Value Strategy	64.2%	60.8%	2.03	Different
z	10.99	6.28		
Result	Different	Different		

The two-tailed proportion tests (Table 6) revealed significant differences (at a significance level of 5%) across all pairs of surfaces. The relative sizes of the *z*-values showed the differences to be larger across strategy type (i.e. growth vs. value strategies) than across the industry scaling variable. The proportion of positive returns were higher for the value strategies than they were for the growth strategies, though the differences were not as pronounced as they were between the winner and loser mean reversion strategies (in section 4.2.3).

Table 7: Mean excess returns of each P/E strategy surface and significant differences

	No Industry Scaling	Industry Scaling	t	Result
Growth Strategy	Mean = -0.63% Std dev = 1.65%	Mean = -0.36% Std dev = 1.90%	4.40	Different
Value Strategy	Mean = -0.09% Std dev = 2.00%	Mean = -0.19% Std dev = 1.76%	1.57	Not different
t	8.53	2.65		
Result	Different	Different		

The two-tailed test for equal means (Table 7) revealed significant differences (at a significance level of 5%) across three of the four pairs of surfaces; the addition of industry scaling to the value strategy did not significantly alter the surface's mean returns.

Table 8: Distribution of sample returns at P/E growth and value strategy surface peaks

						95% Confidence Limits	
Surface	Industry Scaling	Size (shares)	Holding (days)	Return (%)	Standard Deviation (%)	Lower (%)	Upper (%)
Growth Strategy	No	15	340	3.7	21.3	-3.9	11.3
	Yes	25	305	6.1	15.3	0.6	11.5
Value strategy	No	10	60	9.7	125.7	-35.3	54.7
	Yes	30	60	7.1	32.6	-4.5	18.8

In terms of the distribution of the points of maximum return on each surface (Table 8) it is clear that the addition of industry scaling to a P/E growth strategy is desirable as it had the effect of increasing returns (from 3.7% to 6.1%) while simultaneously decreasing the standard deviation of those returns (and therefore narrowing the 95% confidence limits).

The preferable strategy is less obvious in the case of the value strategy, where the addition of industry scaling had the effect of decreasing both the maximum returns generated (from 9.7% to 7.1%) and greatly decreasing the standard deviation (from 125.7% to 32.6%). On the face of it an investor may be inclined to employ industry scaling, and in so doing sacrifice some returns for the large decrease in variability. However, referring back to Figures 15 and 16, one needs to consider that several of the largest returns were found to be isolated peaks on the surfaces, suggesting that they may have been the result of outliers in the data. Therefore, instead of choosing the points in Table 8, an investor would be better served by selecting other, more auto-correlated points on the surfaces (i.e. a point surrounded by other points exhibiting similar returns) on which to base a trading strategy, as doing so would increase the chances of such a strategy successfully replicating the results demonstrated in this research.

Table 9: Distribution of sample returns at points of maximum stable return on P/E growth and value strategy surfaces

						95% Confidence Limits	
Surface	Industry Scaling	Size (shares)	Holding (days)	Return (%)	Standard Deviation (%)	Lower (%)	Upper (%)
Growth Strategy	No	20	340	2.7	18.3	-3.8	9.3
	Yes	25	305	6.1	15.3	0.6	11.5
Value strategy	No	25	235	5.2	15.1	-0.2	10.6
	Yes	30	235	4.5	13.0	-0.2	9.1

Table 9 describes the points of highest return that remained when points that were not surrounded by adjacent points of similarly high returns were disregarded.

As the growth strategy surfaces were relatively well auto-correlated to begin with, the points of maximum return and associated confidence intervals did not change much if at all. This was not the case with the value strategies, where applying the smooth surface selection criterion resulted in both returns and their variability lowering appreciably. A lower return and a smaller upper confidence interval limit confirmed that the addition of industry scaling does not improve the returns generated by a P/E value strategy.

4.3.4 Book-to-market growth strategy

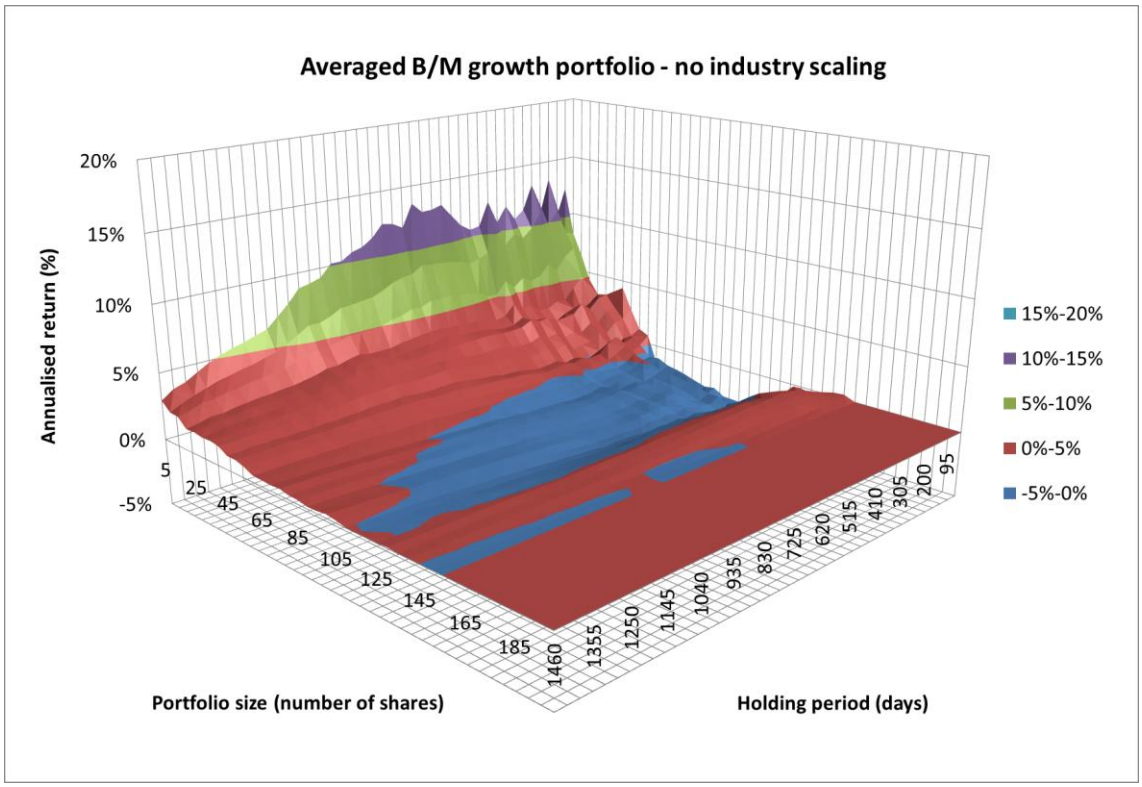


Figure 19: Excess returns generated by B/M growth strategy - no industry scaling

A B/M growth strategy without industry scaling (Figure 19) created a generally smooth, auto-correlated surface of excess returns that peaked briefly with a portfolio size of 5 shares (the minimum portfolio size tested), and quickly dropped to a plateau as portfolio size increased. The surface was visibly rougher for shorter holding periods. For periods shorter than approximately 800 days, holding period seemed to have little effect on portfolio returns, however, as holding period increased from approximately 800 days to the maximum 1,460 days, returns decreased. A maximum average excess return of 13.6% was achieved with a portfolio size of 5 shares and a holding period of 655 days. An area of negative returns, running between portfolio sizes of 55 and 120 shares, reached a minimum excess return of -4.6% with a portfolio size of 100 shares and a holding period of 25 days.

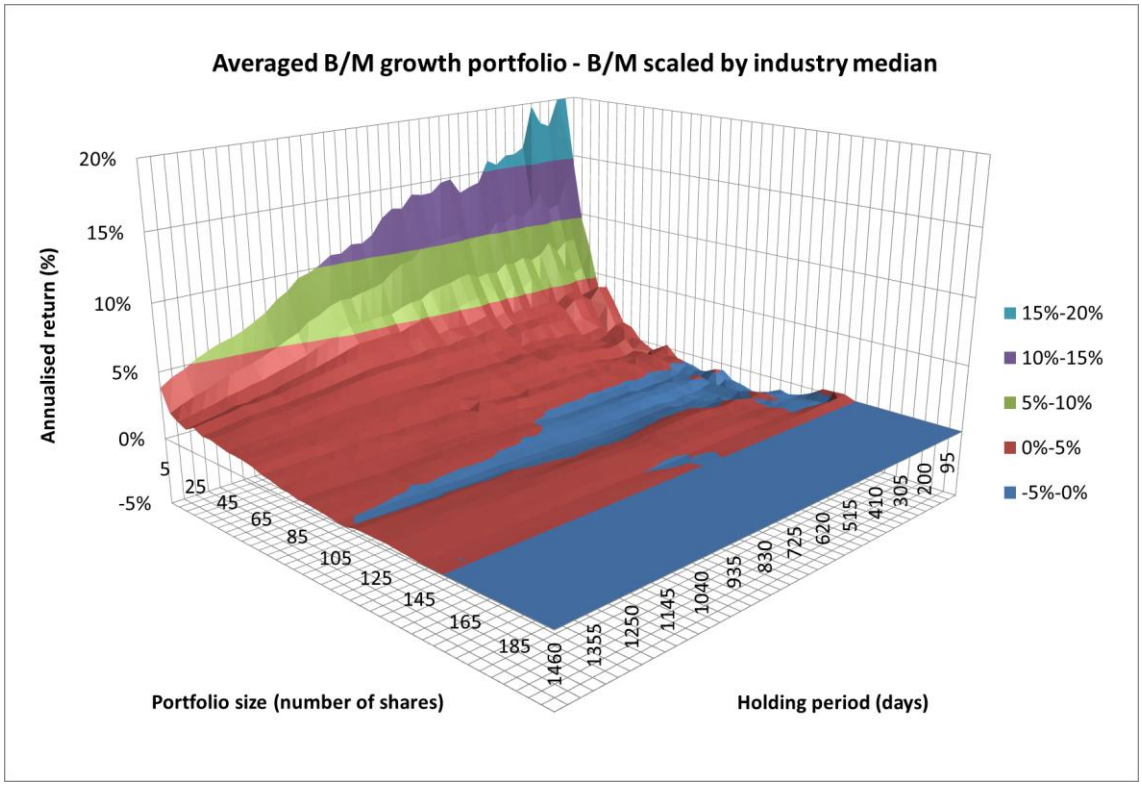


Figure 20: Excess returns generated by B/M growth strategy - B/M scaled by industry median

The addition of industry scaling to a B/M growth strategy (Figure 20) increased the returns achieved for small holding periods, particularly those with holding periods less than 800 days, while leaving the shape of the remainder of the surface largely unchanged. The area of negative returns narrowed to run between portfolio sizes of 55 and 120 shares, reaching a minimum return of -3.3% with a portfolio size of 105 shares and a holding period of 25 days. A maximum average excess return of 26.5% was achieved with a portfolio size of 5 shares and a holding period of 60 days.

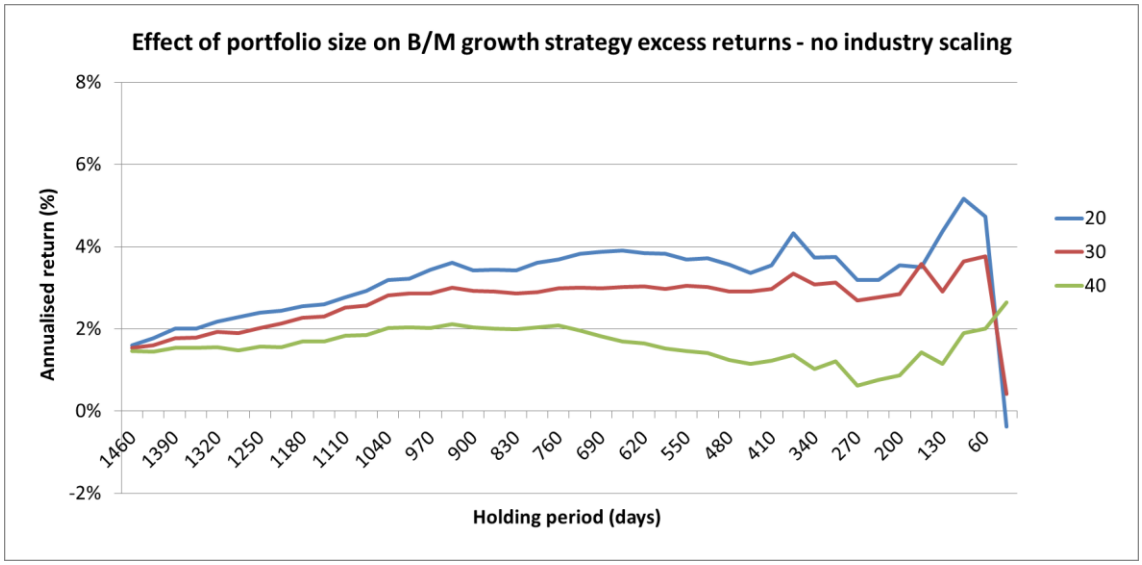


Figure 21: Effect of portfolio size on B/M growth strategy excess returns - no industry scaling

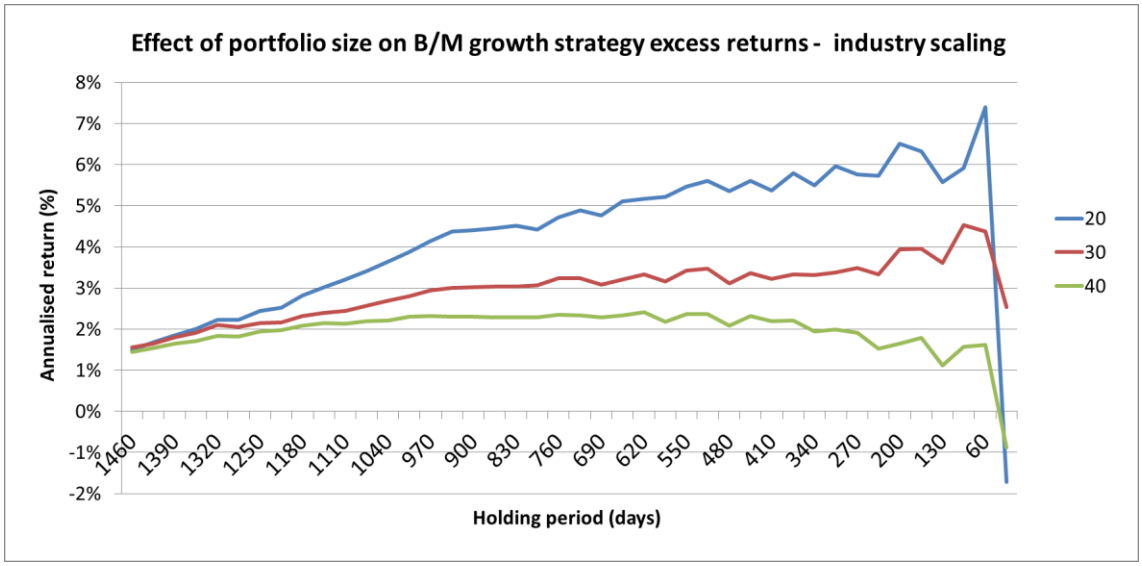


Figure 22: Effect of portfolio size on B/M growth strategy excess returns - B/M scaled by industry median

The 20, 30 and 40-share cross-sections (Figures 21 and 22) revealed that only the smaller portfolios benefitted from the addition of industry scaling to the B/M growth strategy: the returns generated by the 20-share portfolio increased visibly across all holding periods, while those of the 30 and 40-share portfolios appeared largely unchanged.

4.3.5 Book-to-market value strategy

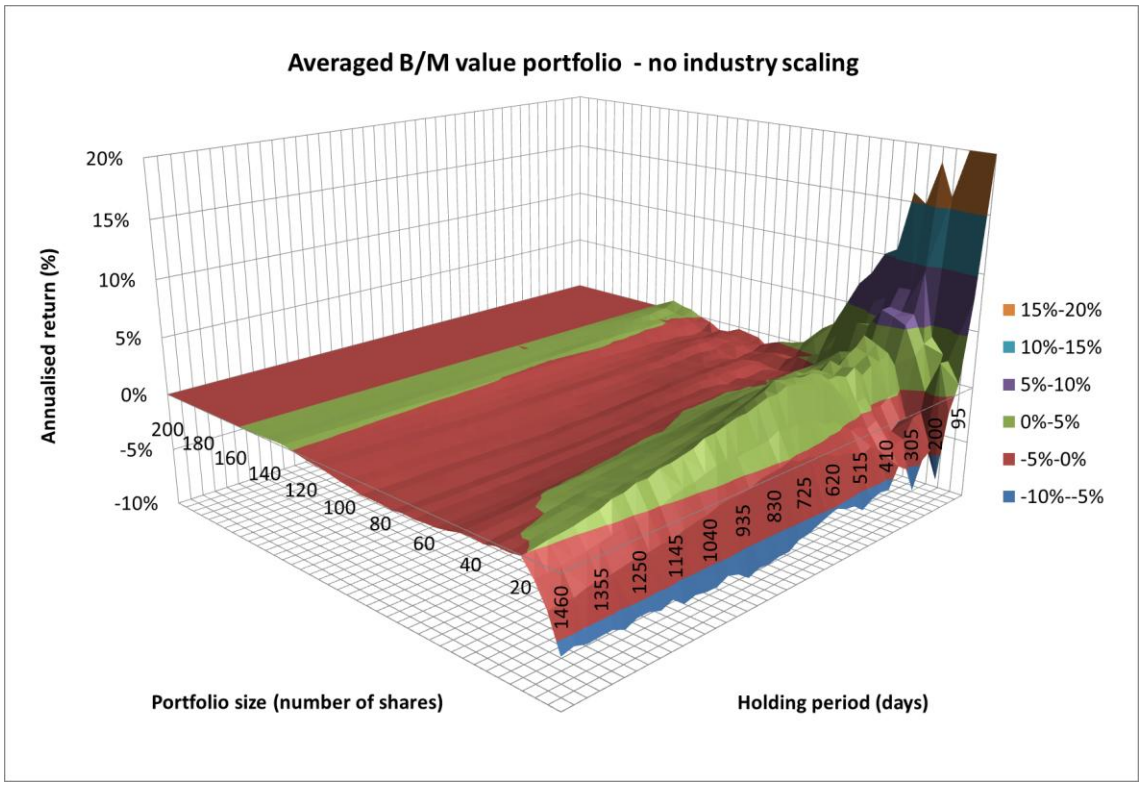


Figure 23: Excess returns generated by B/M value strategy - no industry scaling

The surface created by a B/M value strategy without industry scaling (Figure 23) resembled that created by a P/E value strategy (also without industry scaling). Returns were negative over the majority of the surface, with the exception of a long, narrow ridge of positive returns that extended across almost all holding periods for portfolio sizes of between 20 and 50 shares. Returns dipped steeply negative for portfolios of less than 20 shares. The largest returns were generated by portfolios with the fewest number of shares and shortest holding periods. A maximum average excess return of 34.1% was achieved with a portfolio size of 5 shares and a holding period of 25 days.

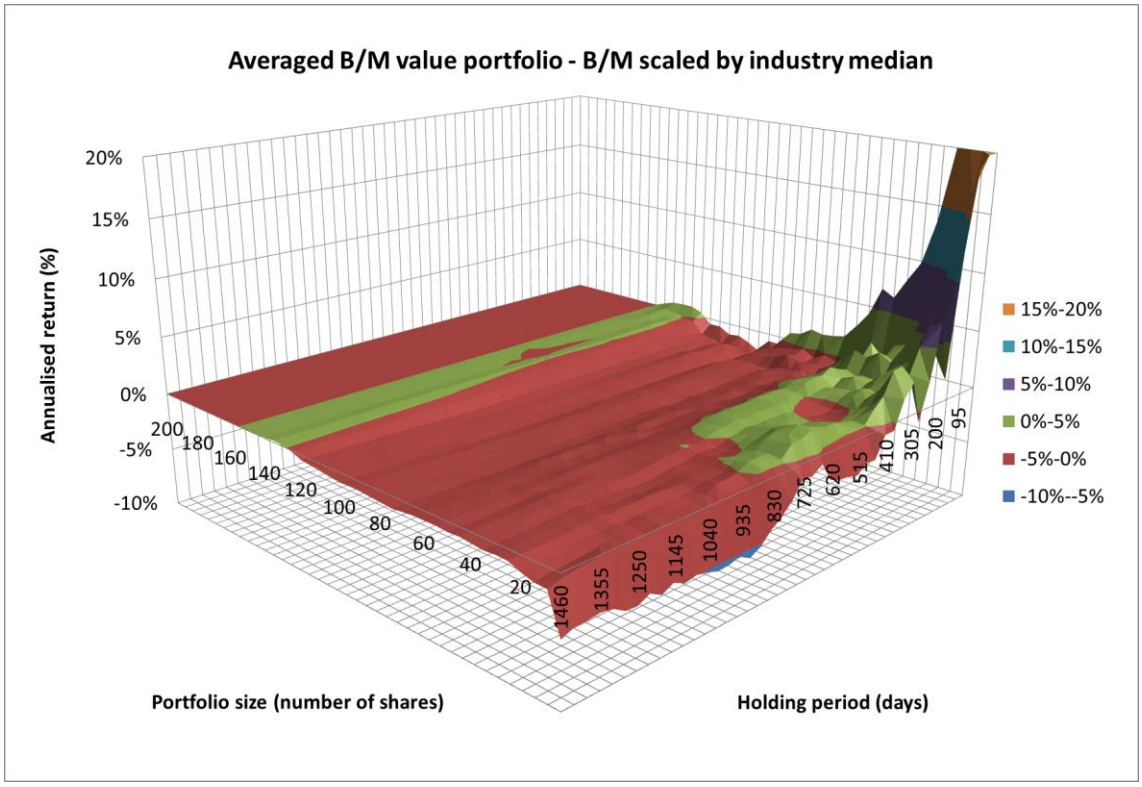


Figure 24: Excess returns generated by B/M value strategy - B/M scaled by industry median

The addition of industry scaling to the B/M value strategy (Figure 24) effectively removed the long, narrow ridge of positive returns. The only meaningfully positive returns remaining were generated by small portfolios with low holding periods. A maximum average excess return of 41.5% was achieved with a portfolio size of 5 shares and a holding period of 25 days.

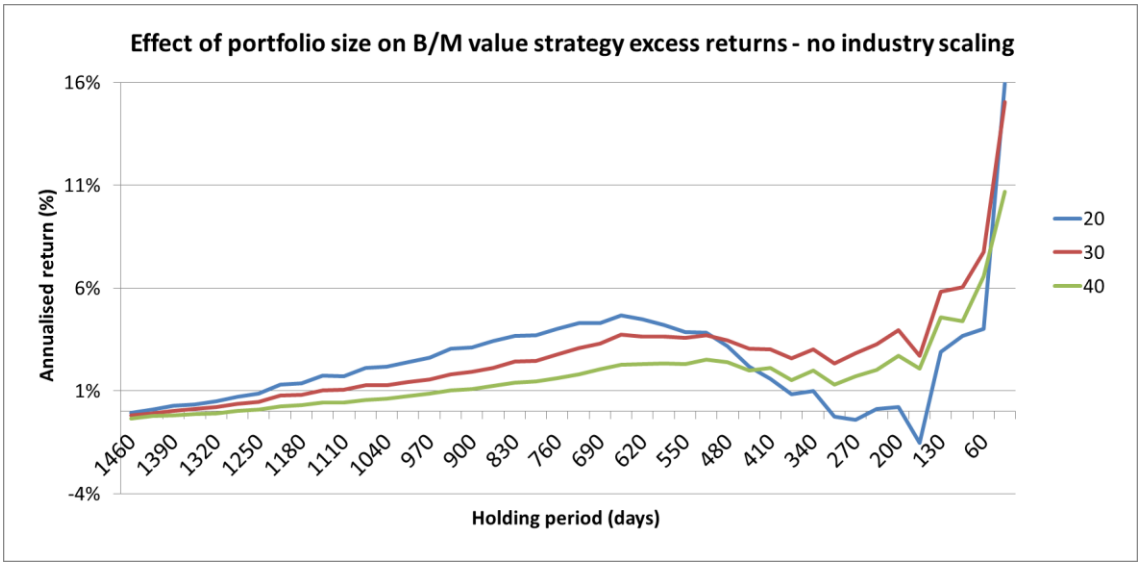


Figure 25: Effect of portfolio size on B/M value strategy excess returns - no industry scaling

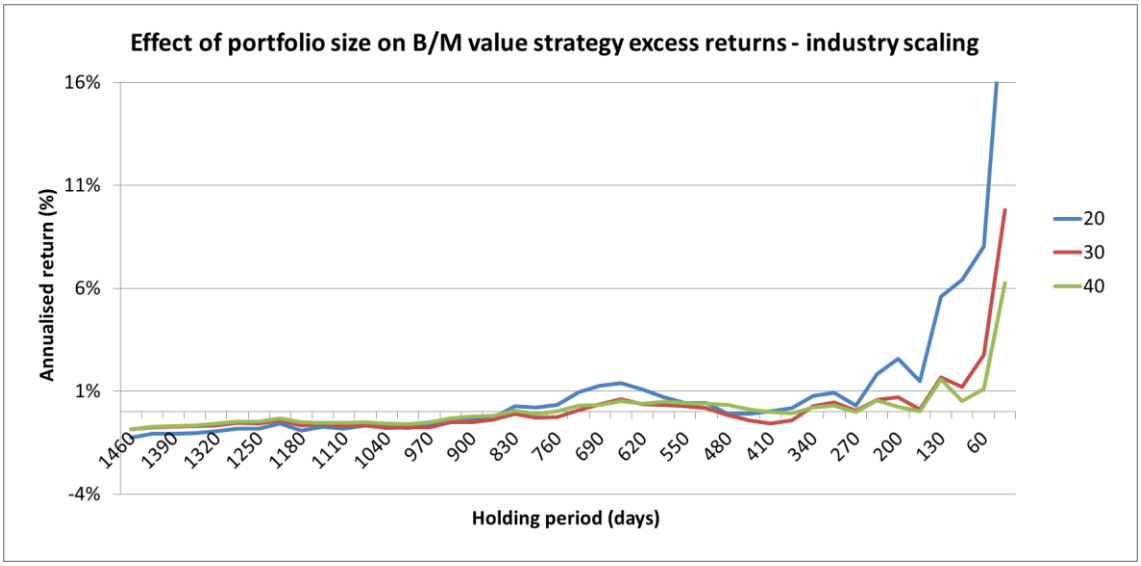


Figure 26: Effect of portfolio size on B/M value strategy excess returns - B/M scaled by industry median

The 20, 30 and 40-share cross-sections (Figures 25 and 26) confirmed the observations made using the surface charts. The application of industry scaling virtually eliminated meaningful positive returns for holding periods greater than 340 days across all three portfolio sizes. The 20-share portfolio was the only one that benefited from the inclusion of industry scaling over any holding period, and even this only happened for holding periods less than 340 days.

It was noted that in the case of a B/M value strategy without industry scaling, a 20-share portfolio generated excess returns of approximately 4% for all holding periods between 500 and 800 days.

4.3.6 Book-to-market strategy statistical tests

Table 10: Proportion positive of each B/M strategy surface and significant differences

	No Industry Scaling	Industry Scaling	z	Result
Growth Strategy	70.6%	83.4%	8.81	Different
Value Strategy	55.5%	47.1%	4.91	Different
z	9.04	22.10		
Result	Different	Different		

The two-tailed proportion tests (Table 10) revealed significant differences (at a significance level of 5%) across all four pairs of surfaces. As was the case with the P/E strategies, the relative sizes of the *z*-values showed the differences to be larger across strategy type (i.e. growth vs. value strategies) than across the industry scaling variable. The addition of industry scaling increased the proportion of positive excess returns on the growth strategy surface, and decreased the proportion of positive excess returns on the value strategy surface.

Table 11: Mean excess returns of each B/M strategy surface and significant differences

	No Industry Scaling	Industry Scaling	t	Result
Growth Strategy	Mean = 0.73% Std dev = 2.29%	Mean = 1.15% Std dev = 2.69%	4.90	Different
Value Strategy	Mean = 0.03% Std dev = 2.21%	Mean = -0.21% Std dev = 2.25%	3.07	Different
t	9.02	15.87		
Result	Different	Different		

The two-tailed test for equal means (Table 11) also revealed significant differences (at a significance level of 5%) across all four pairs of surfaces. Of the four, the B/M growth strategy with industry scaling exhibited the largest mean excess returns (1.15%).

Table 12: Distribution of sample returns at B/M growth and value strategy surface peaks

						95% Confidence Limits	
Surface	Industry Scaling	Size (shares)	Holding (days)	Return (%)	Standard Deviation (%)	Lower (%)	Upper (%)
Growth Strategy	No	5	655	13.6	21.2	6.0	21.2
	Yes	5	60	26.5	66.6	2.7	50.4
Value strategy	No	5	25	34.1	368.0	-97.6	165.8
	Yes	5	25	41.5	378.2	-93.8	176.8

According to the distribution of points of maximum return (Table 12), the addition of industry scaling to a B/M growth strategy almost doubles portfolio

return at the point of maximum return (from 13.6% to 26.5%). Standard deviation also increases (from 21.2% to 66.6%), however, as the lower 95% confidence limit remains positive (decreasing only marginally from 6.0% to 2.7%), even with the increased variability the addition of industry scaling is likely to be preferred by a rational investor.

Using this same rationale, the B/M value strategy would also be preferable with the addition of industry scaling (to a B/M value strategy without industry scaling). However, as was the case with the P/E value strategy, the maximum return is located on the tip of a pinnacle on the surface chart (see Figure 24), so an investor would, in all likelihood, be better served by choosing a portfolio on a more auto-correlated portion of the surface. A well auto-correlated area of meaningful positive returns does not exist on the B/M value strategy surface when industry scaling is applied, meaning that a B/M value strategy without industry scaling would instead be preferable.

Table 13: Distribution of sample returns at points of maximum stable return on B/M growth and value strategy surfaces

						95% Confidence Limits	
Surface	Industry Scaling	Size (shares)	Holding (days)	Return (%)	Standard Deviation (%)	Lower (%)	Upper (%)
Growth Strategy	No	10	200	11.0	25.0	2.1	19.9
	Yes	10	95	12.9	31.7	1.5	24.2
Value strategy	No	35	130	6.2	15.3	0.7	11.7
	Yes	15	200	3.3	21.2	-4.3	10.9

Disregarding points of high return that were not surrounded by adjacent points of similar returns (Table 13) had the effect of reducing the maximum returns in both the growth strategy surfaces. However, while standard deviation decreased for the second surface (i.e. with the application of industry scaling) it

increased for the first, thus confirming that a B/E growth strategy with industry scaling is preferable to the same strategy without industry scaling.

Ignoring irregular peaks had the effect drastically reducing the maximum returns and standard deviations on the B/M value strategy surfaces; with a higher maximum return and a positive lower confidence limit value, the B/M value strategy without industry scaling was again shown to be preferable to the B/M value strategy with industry scaling.

4.3.6 Hypothesis 2 conclusion

The hypothesis tested in this section was as follows:

H_0: An optimised value strategy that exploits the P/E effect or the B/M effect will not outperform the market.

H_a: An optimised value strategy that exploits the P/E effect or the B/M effect will outperform the market

Visual inspection of both the P/E and B/M value strategy charts revealed that optimised test portfolios were able to generate significant excess returns over a relatively wide range of holding periods. The statistical tests, for the reasons explained in section 3.3.6, did not add much in terms of providing evidence towards testing hypothesis 2. When points of high return that were not surrounded by adjacent points of similar returns were disregarded, each of the optimised strategies generated meaningful positive average excess returns. Therefore, based on the above evidence, and assuming that past events are a predictor of future share price behaviour, we must reject the null hypothesis in favour of the alternate hypothesis, and conclude that an optimised value strategy that exploits the P/E effect or the B/M effect will outperform the market.

4.4 Results pertaining to Hypothesis 3

In an attempt to maximise the probability of obtaining meaningful results while still performing a reasonable number of simulations, the following lessons learned in sections 4.3 and 4.3 were incorporated into the choice of combined trading strategies that were tested:

a) As growth and value strategies had been shown to only generate positive excess returns for relatively small portfolio sizes, it was decided to simulate 20, 30 and 40-share portfolios. (Winner and loser strategies generated positive excess returns over a greater range of portfolios sizes).
b) For similar reasons, it was decided to employ industry scaling for the combined winner/growth strategies, but not for the combined loser/value strategies.

4.4.1 Visual inspection of the test surfaces

In order to test Hypothesis 3, 36 test surfaces were generated, 9 for each of the combined trading strategies. These surfaces may be found in Tables 14 through 17. Rather than describe each surface individually, common themes and notable observations are briefly discussed.

In all cases, increasing the size of the portfolios tended to both smoothen and flatten the surfaces, reducing any pinnacles of high returns and increasing the degree of auto-correlation apparent in the surfaces.

As can be seen in the left hand column of each of the table, when the P/E and B/M restrictions were at their least severe (i.e. when only 25% of the shares were ineligible for inclusion in the winner and loser portfolios because their P/E or B/M ratio had exceeded the cut-off threshold), the surfaces shapes closely resembled those of their equivalent pure mean reversion surfaces, but were slightly flatter. For example the surface in the middle left cell of Table 11, the combined P/E winner/growth strategy, resembled a slightly flattened version of the 30-share winner surface in Figure 5.

Table 14: Excess returns generate by combined P/E winner/growth strategy - P/E scaled by industry median

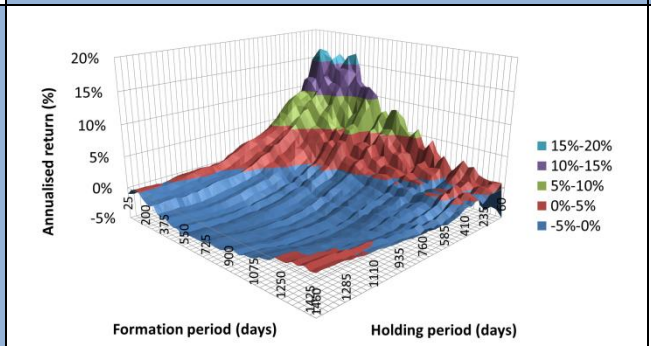
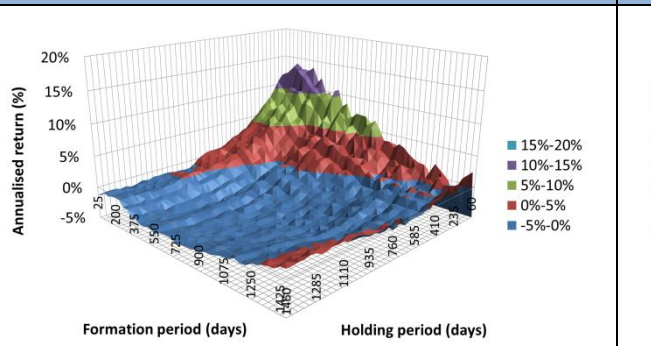
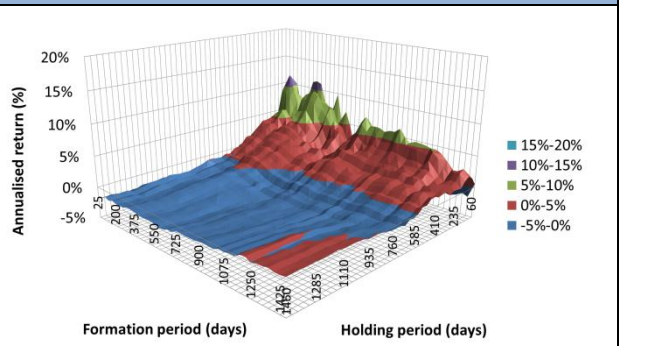
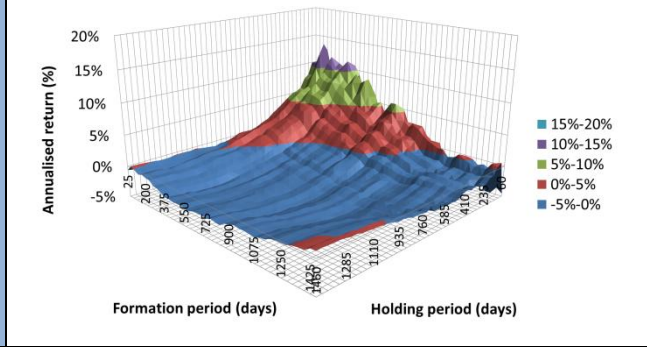
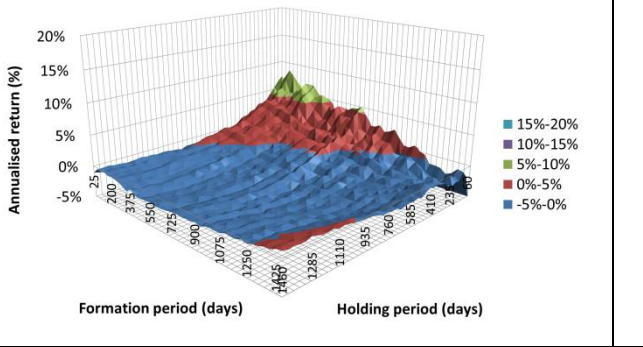
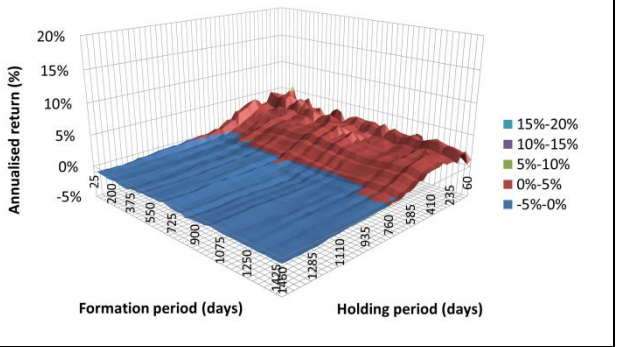
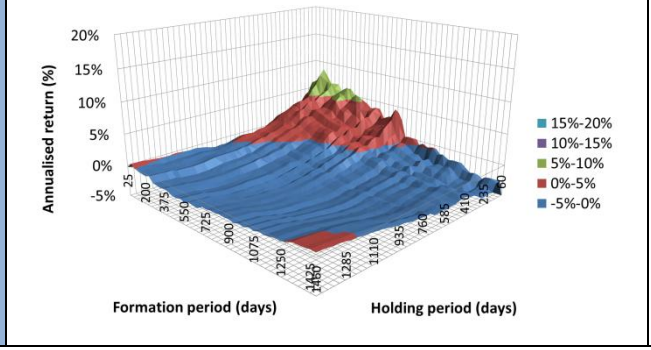
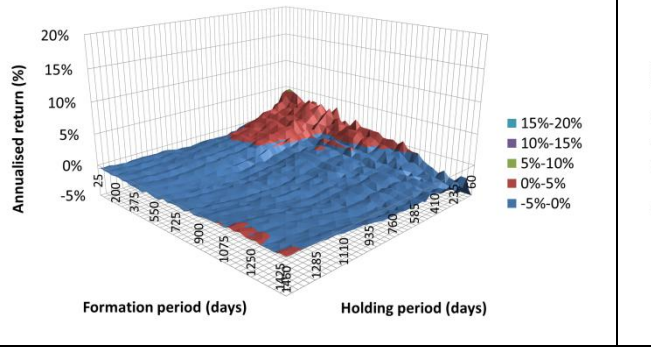
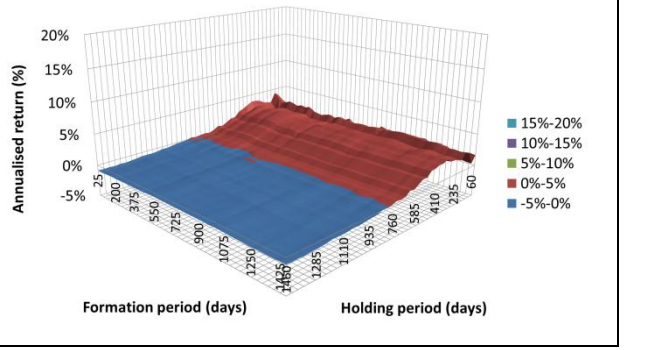
	P/E in upper 75%	P/E in upper 50%	P/E in upper 25%
20-share portfolio			
30-share portfolio			
40-share portfolio			

Table 15: Excess returns generated by combined P/E loser/value strategy - no industry scaling

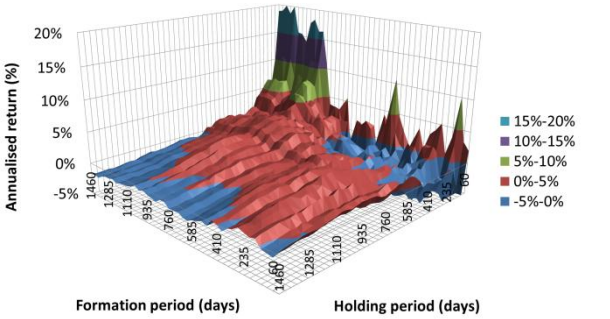
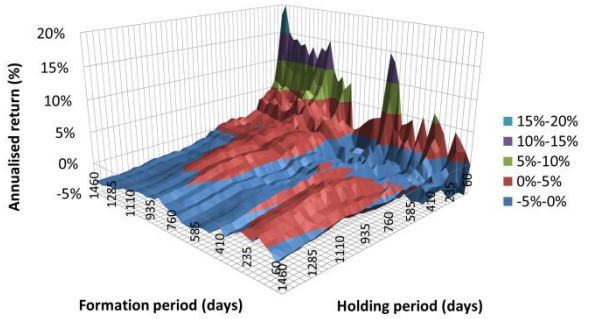
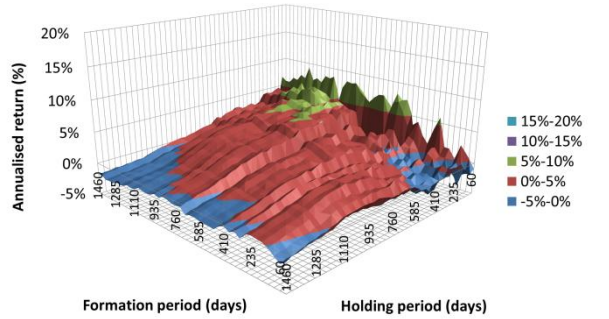
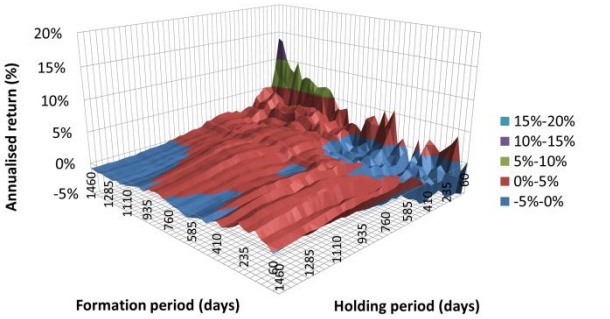
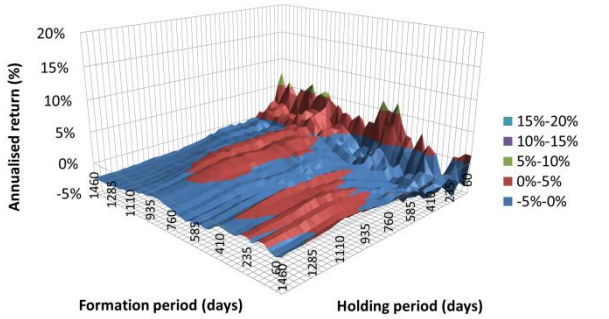
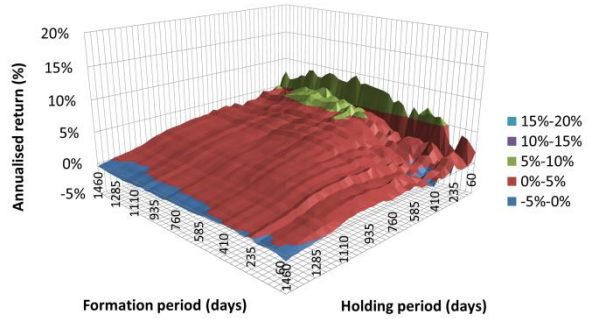
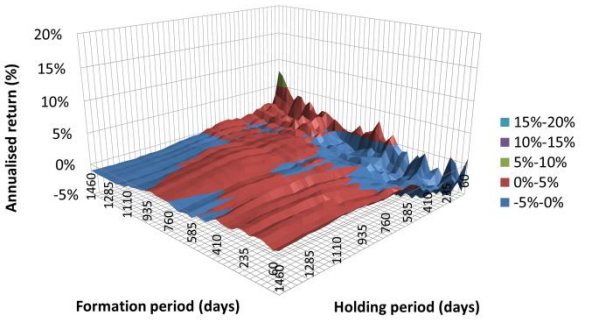
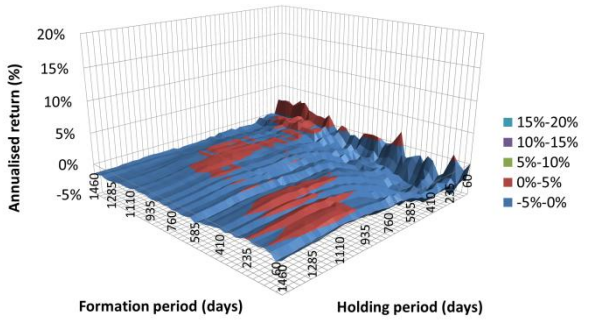
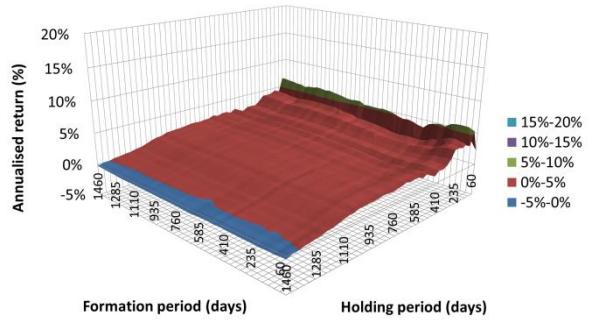
	P/E in lower 75%	P/E in lower 50%	P/E in lower 25%
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30-share portfolio			
40-share portfolio			

Table 16: Excess returns generated by combined B/M winner/growth strategy – B/M scaled by industry median

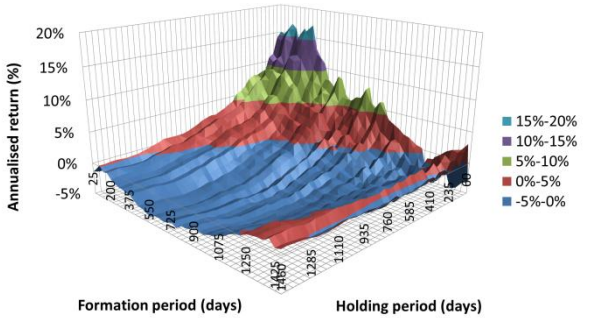
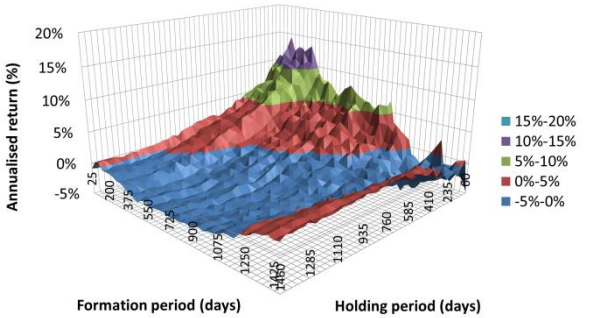
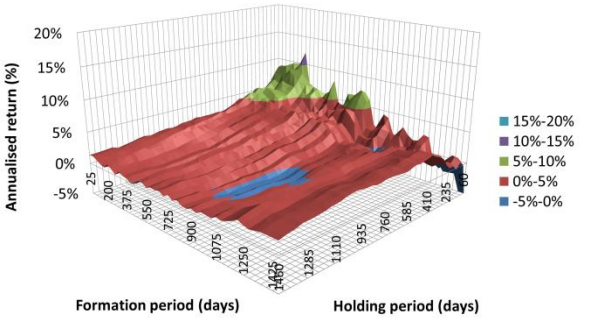
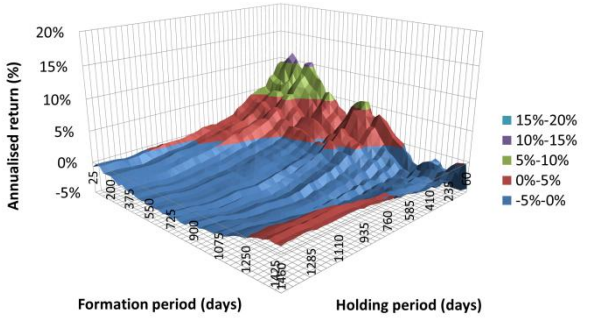
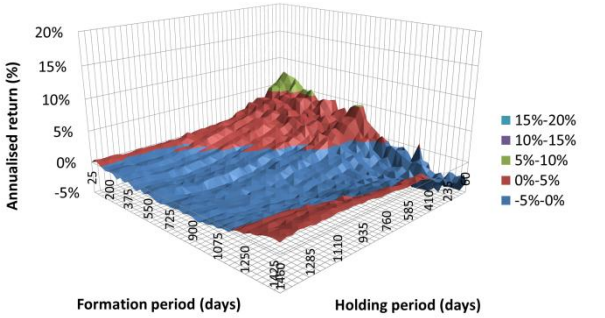
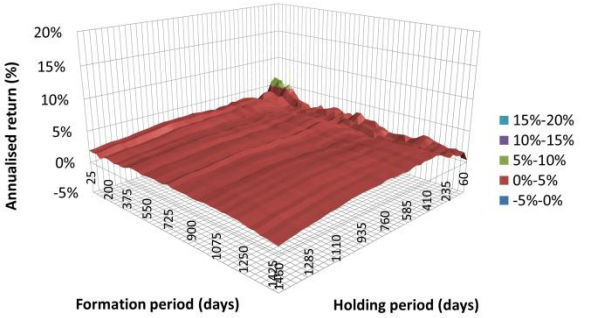
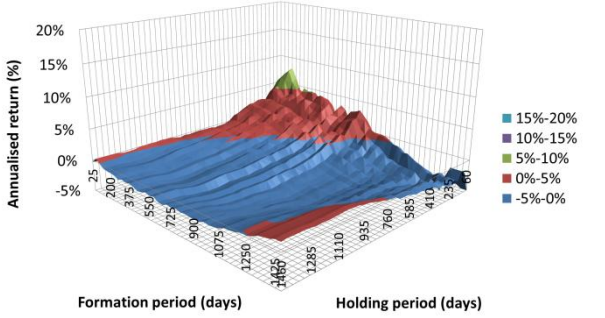
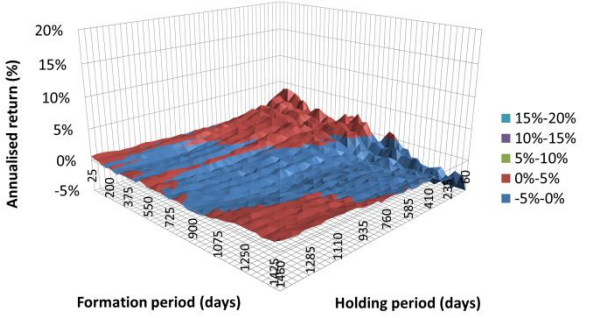
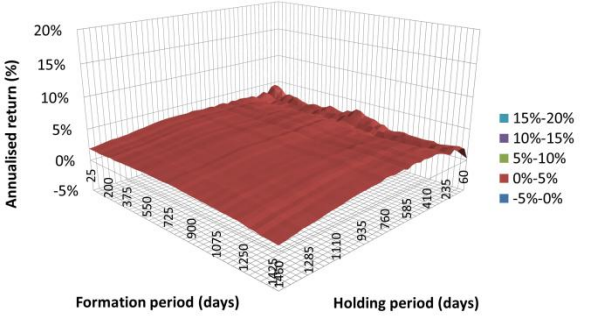
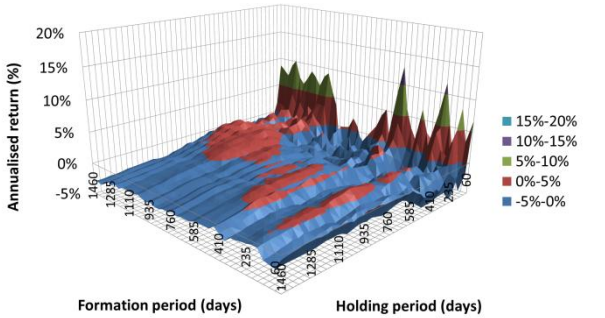
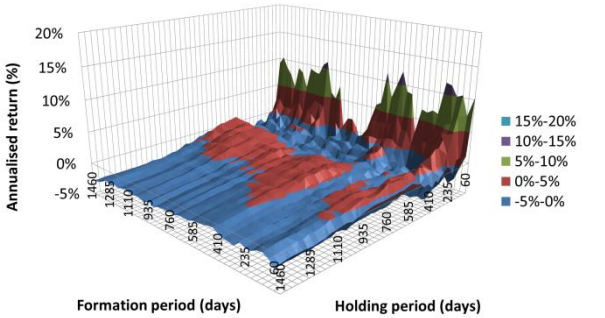
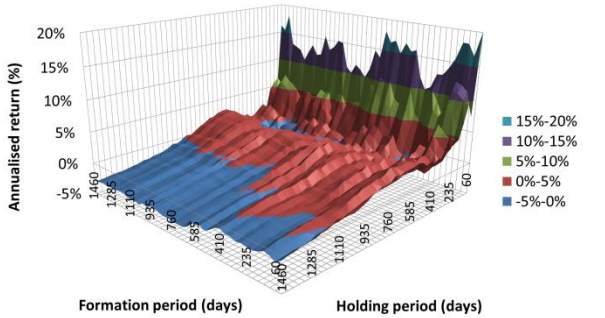
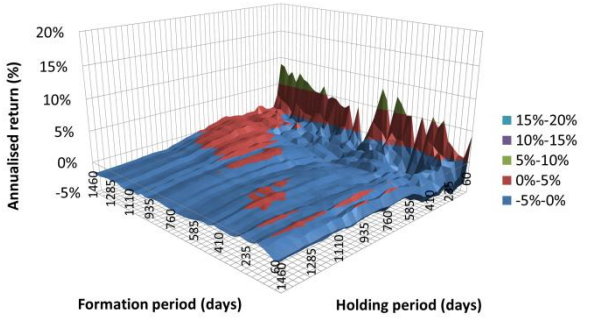
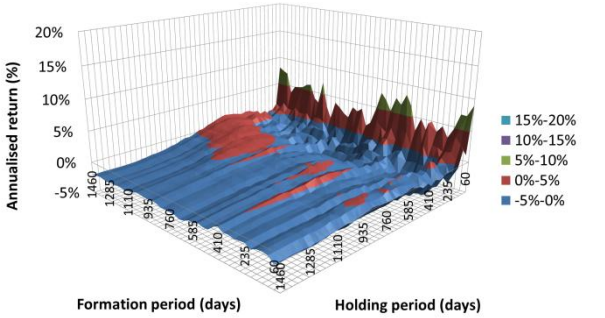
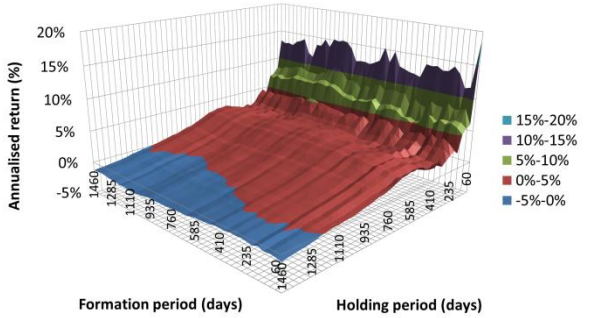
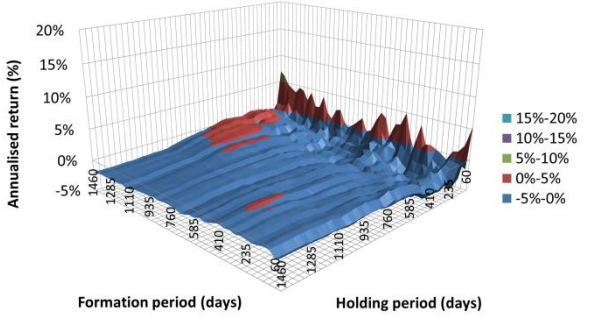
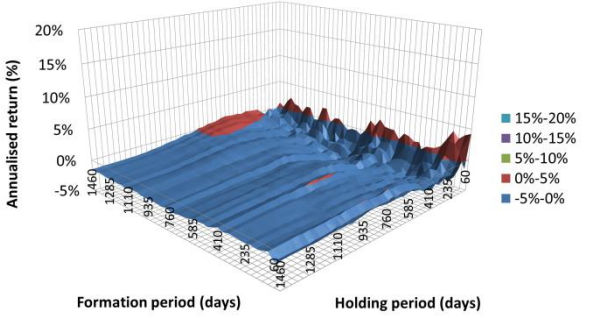
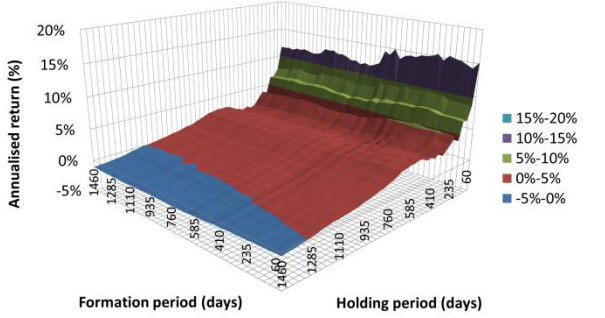
	B/M in lower 75%	B/M in lower 50%	B/M in lower 25%
20-share portfolio			
30-share portfolio			
40-share portfolio			

Table 17: Excess returns generated by combined B/M loser/value strategy – no industry scaling

	B/M in upper 75%	B/M in upper 50%	B/M in upper 25%
20-share portfolio			
30-share portfolio			
40-share portfolio			

Turning attention to the right hand column of each table, it is evident that when the P/E and B/M restrictions were at their most severe (i.e. when a full 75% of the shares were ineligible for inclusion in the winner and loser portfolios because their P/E or B/M ratio had exceeded the cut-off threshold), the surfaces closely resembled those of their equivalent pure growth or value strategies. As one would expect, because these surfaces were mostly shaped by the P/E and B/M trading rules, formation period appeared to have little effect on portfolio return.

Based on an inspection of the surfaces, it was decided to limit statistical comparisons to the most promising combinations of portfolio sizes and strategies, namely 20 and 30-share portfolios with 75% and 25% P/E and B/M thresholds. This necessitated the running of a further set of pure mean reversion winner and loser simulations, this time holding the portfolio size constant at 20 shares. The resulting surfaces are depicted in Figures 27 and 28.

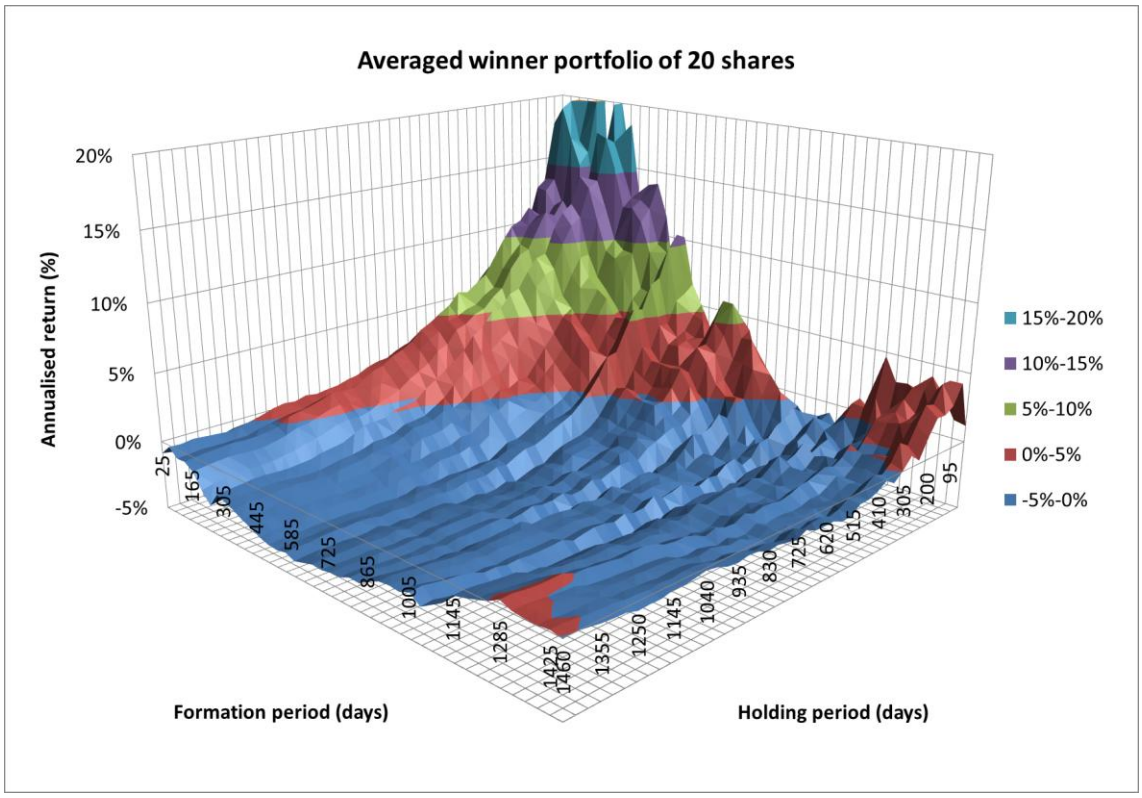


Figure 27: Excess returns generated by 20-share winner strategy

When comparing the pure winner strategy surface (Figure 27) to the equivlent combined 75% strategy surfaces (i.e. the top left surfaces in Tables 14 and 16), one can see that the shapes of the surfaces are all very similar, but the peak excess return achieved in the corner of lowest formation and holding periods is larger in the case of the pure mean reversion surface than it is for the other two strategies.

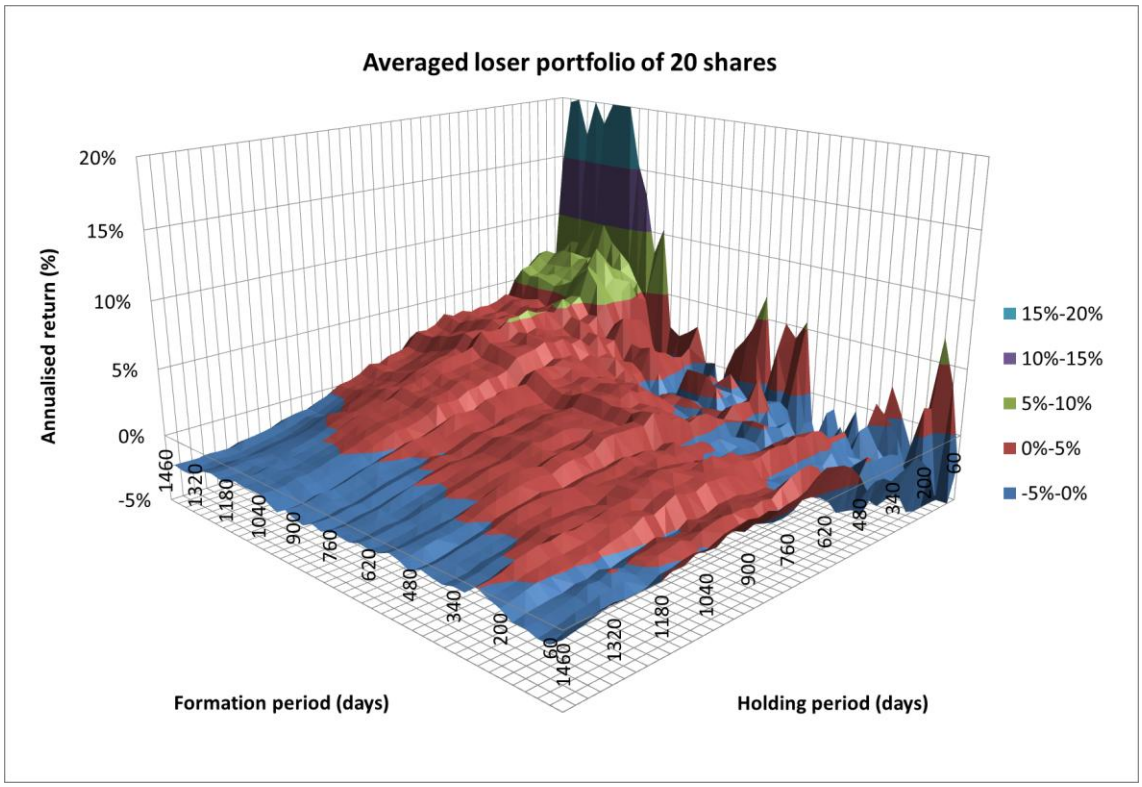


Figure 28: Excess returns generated by 20-share loser strategy

When comparing the pure loser strategy surface (Figure 28) to the equivalent combined 25% strategy surfaces (i.e. the top left surfaces in Tables 15 and 17), the results are more interesting: in the case of the combined P/E loser/value strategy the surfaces are almost identical, however, in the case of the combined B/M loser/value strategy, most of the excess returns appeared to have been eliminated by the inclusion of the B/M threshold rule.

4.4.2 Difference-in-proportion tests

Table 18: Proportion positive of each 75% combined strategy surface and significant differences

	Portfolio Size	Combined strategy	Pure Mean Reversion Strategy	z	Result
Combined P/E Winner/Growth Strategy	20 Shares	36.3%	28.4%	5.04	Different
	30 Shares	27.5%	36.7%	5.88	Different
Combined P/E Loser/Value Strategy	20 Shares	65.8%	62.9%	1.83	Not Different
	30 Shares	68.1%	65.2%	1.82	Not Different
Combined B/M Winner/Growth Strategy	20 Shares	34.8%	28.4%	4.09	Different
	30 Shares	29.5%	36.7%	4.54	Different
Combined B/M Loser/Value Strategy	20 Shares	28.5%	62.9%	20.48	Different
	30 Shares	22.6%	65.2%	25.51	Different

The two-tailed proportion tests (see Table 18) revealed significant differences (at a significance level of 5%) across 6 of the 8 pairs of 75% combined strategy surfaces. For both combined winner/growth strategies, the 20-share surfaces exhibited a larger proportion of positive returns (between 6 & 10% larger) in the case of the combined strategy than they did in the case of the pure mean reversion strategy, however, the situation was reversed when the portfolio sizes were increased to 30 shares. As one would have expected after viewing the surfaces, in terms of proportions of positive excess returns, the combined B/M loser/value strategy was vastly inferior to the equivalent pure mean reversion strategy for both portfolio sizes.

Table 19: Proportion positive of each 25% combined strategy surface and significant differences

	Portfolio Size	Combined strategy	Pure Mean Reversion Strategy	z	Result
Combined P/E Winner/Growth Strategy	20 Shares	42.7%	28.4%	8.86	Different
	30 Shares	43.5%	36.7%	4.12	Different
Combined P/E Loser/Value Strategy	20 Shares	77.6%	62.9%	9.57	Different
	30 Shares	91.9%	65.2%	19.32	Different
Combined B/M Winner/Growth Strategy	20 Shares	91.5%	28.4%	38.24	Different
	30 Shares	100.0%	36.7%	40.40	Different
Combined B/M Loser/Value Strategy	20 Shares	63.7%	62.9%	0.52	Not Different
	30 Shares	78.2%	65.2%	8.56	Different

The two-tailed proportion tests in Table 19 revealed that, in terms of proportion of positive excess returns, the 25% combined strategies were superior to their equivalent pure mean reversion strategies in every case (though in one case the difference was not significant). This finding is not unexpected, as it was already observed that the 25% combined strategy surfaces closely resembled their equivalent growth and value surfaces in section 4.3 of this study (or to be precise Figures 12, 15, 20 and 23), and that for small portfolio sizes, those growth and value strategy surfaces had exhibited positive returns over a wide range of holding periods.

4.4.3 Difference-in-mean tests

Table 20: Mean excess returns of each 75% combined strategy surface and significant differences

	Portfolio Size	Combined strategy	Pure Mean Reversion Strategy	t	Result
Combined P/E Winner/Growth Strategy	20 Shares	0.10%	-0.14%	1.81	Not Different
	30 Shares	-0.50%	0.18%	6.17	Different
Combined P/E Loser/Value Strategy	20 Shares	0.90%	0.91%	0.10	Not Different
	30 Shares	0.57%	0.76%	3.06	Different
Combined B/M Winner/Growth Strategy	20 Shares	-0.29%	-0.14%	1.08	Not Different
	30 Shares	-0.80%	0.18%	9.18	Different
Combined B/M Loser/Value Strategy	20 Shares	-0.57%	0.91%	20.07	Different
	30 Shares	-0.56%	0.76%	23.15	Different

The difference-in-mean tests (the results of which are listed in Table 20) revealed that the average excess returns generated by the 75% combined strategies were almost always lower than those generated by their equivalent pure mean reversion strategies (the one exception being the 20-share combined P/E winner/growth strategy). With the exception of the combined B/M loser/value strategy, the differences in means were significant (at a significance level of 5%) for the 30-share surfaces, but not for the 20-share surfaces.

Table 21: Mean excess returns of each 25% combined strategy surface and significant differences

	Portfolio Size	Combined strategy	Pure Mean Reversion Strategy	t	Result
Combined P/E Winner/Growth Strategy	20 Shares	0.30%	-0.14%	3.86	Different
	30 Shares	0.47%	0.18%	3.13	Different
Combined P/E Loser/Value Strategy	20 Shares	1.80%	0.91%	11.06	Different
	30 Shares	2.43%	0.76%	25.59	Different
Combined B/M Winner/Growth Strategy	20 Shares	2.01%	-0.14%	19.68	Different
	30 Shares	1.05%	0.18%	10.02	Different
Combined B/M Loser/Value Strategy	20 Shares	1.05%	0.91%	1.50	Not Different
	30 Shares	2.21%	0.76%	17.62	Different

As was the case with the proportion tests, when considered in terms of mean returns the 25% combined strategies were once again overwhelmingly superior to their equivalent pure mean reversion strategies (see Table 21); in all cases the combined strategy mean returns were greater than the pure mean reversion returns, and these differences in means were statistically significant in 7 out of 8 of the tests.

4.4.4 Distribution of sample returns

Tables 22 and 23 list the peak excess returns, together with their standard deviations and 95% confidence limits, generated by the various combined and pure-mean reversion trading strategies.

Table 22: Distribution of sample returns at 75% combined strategy surface peaks

						95% Confidence Limits	
Surface	Shares Included (%)	Formation (days)	Holding (days)	Return (%)	Standard Deviation (%)	Lower (%)	Upper (%)
Pure Mean Reversion Winner Strategy	20	200	25	25.5	69.7	0.5	50.4
	30	165	60	18.5	32.1	7.1	30.0
Combined P/E Winner/Growth Strategy	20	95	95	14.0	27.1	4.3	23.7
	30	165	95	14.1	21.4	6.5	21.8
Combined B/M Winner/Growth Strategy	20	340	60	17.4	43.4	1.8	32.9
	30	165	60	11.6	28.1	1.6	21.7
Pure Mean Reversion Loser Strategy	20	1320	25	21.8	95.7	-12.5	56.0
	30	1425	25	16.1	73.4	-10.2	42.3
Combined P/E Loser/Value Strategy	20	1390	25	20.6	97.6	-14.3	55.5
	30	1460	25	13.8	63.0	-8.8	36.3
Combined B/M Loser/Value Strategy	20	480	25	13.0	53.3	-6.1	32.0
	30	1460	25	8.7	46.1	-7.7	25.2

Table 23: Distribution of sample returns at 25% combined strategy surface peaks

Surface	Shares Included (%)	Formation (days)	Holding (days)	Return (%)	Standard Deviation (%)	95% Confidence Limits	
						Lower (%)	Upper (%)
Pure Mean Reversion Winner Strategy	20	200	25	25.5	69.7	0.5	50.4
	30	165	60	18.5	32.1	7.1	30.0
Combined P/E Winner/Growth Strategy	20	95	60	11.8	25.7	2.6	21.0
	30	130	25	5.8	24.7	-3.0	14.7
Combined B/M Winner/Growth Strategy	20	270	25	12.2	37.7	-1.3	25.7
	30	25	60	6.4	13.1	1.7	11.1
Pure Mean Reversion Loser Strategy	20	1320	25	21.8	95.7	-12.5	56.0
	30	1425	25	16.1	73.4	-10.2	42.3
Combined P/E Loser/Value Strategy	20	1215	60	9.5	46.2	-7.0	26.0
	30	830	60	9.9	30.9	-1.1	21.0
Combined B/M Loser/Value Strategy	20	25	25	21.7	57.6	1.1	42.4
	30	25	25	18.7	36.0	5.8	31.6

In most cases the peak returns generated by the combined trading strategies were lower than those generated by their equivalent pure mean reversion strategies. This does not, however, mean that the pure mean reversion strategies are superior, as in almost all the cases the returns generated by the combined strategies exhibited considerably lower variability (i.e. lower standard

deviations and narrower confidence intervals), which means that the combined strategies may still be preferred by an investor.

The one noticeable exception to the above statement was the combined 25% B/M loser/value strategy, which exhibited both similar returns at its peaks than its equivalent pure man reversion loser strategy and lower variability. That said, these peaks occurred at holding periods of just 25 days, so it is likely that the pure mean reversion strategy would have prevailed had trading costs been considered in the calculations.

Table 24: Distribution of sample returns at points of maximum stable return on 75% combined strategy surfaces

Surface	Size (shares)	Formation (days)	Holding (days)	Return (%)	Standard Deviation (%)	95% Confidence Limits	
						Lower (%)	Upper (%)
Pure Mean Reversion Winner Strategy	20	130	95	20.2	33.0	8.4	32.0
	30	165	60	18.5	32.1	7.1	30.0
Combined P/E Winner/Growth Strategy	20	130	130	15.8	31.4	4.5	27.0
	30	235	95	12.0	21.6	4.3	19.8
Combined B/M Winner/Growth Strategy	20	305	95	16.1	38.1	2.5	29.8
	30	165	95	10.9	22.6	2.9	19.0
Pure Mean Reversion Loser Strategy	20	1180	165	8.8	26.2	-0.6	18.2
	30	1355	165	6.3	20.0	-0.9	13.4
Combined P/E Loser/Value Strategy	20	1110	130	7.9	28.0	-2.1	17.9
	30	1390	130	4.5	19.7	-2.6	11.5
Combined B/M Loser/Value Strategy	20	1110	655	1.6	6.1	-0.6	3.8
	30	1320	550	1.7	4.0	0.3	3.1

Table 25: Distribution of sample returns at points of maximum stable return on 25% combined strategy surfaces

Surface	Size (shares)	Formation (days)	Holding (days)	Return (%)	Standard Deviation (%)	95% Confidence Limits	
						Lower (%)	Upper (%)
Pure Mean Reversion Winner Strategy	20	130	95	20.2	33.0	8.4	32.0
	30	165	60	18.5	32.1	7.1	30.0
Combined P/E Winner/Growth Strategy	20	130	95	10.8	20.7	3.4	18.2
	30	130	95	4.6	12.0	0.3	8.9
Combined B/M Winner/Growth Strategy	20	165	25	6.6	34.1	-5.6	18.8
	30	60	95	5.0	10.2	1.4	8.7
Pure Mean Reversion Loser Strategy	20	1180	165	8.8	26.2	-0.6	18.2
	30	1355	165	6.3	20.0	-0.9	13.4
Combined P/E Loser/Value Strategy	20	1075	165	7.2	18.8	0.5	14.0
	30	1040	130	7.1	13.9	2.2	12.1
Combined B/M Loser/Value Strategy	20	130	515	3.4	8.8	0.3	6.6
	30	725	515	4.0	6.3	1.7	6.2

Tables 24 and 25 list the peak excess returns obtained after disregarding points of high return on the surfaces that were not surrounded by adjacent points if similarly high returns.

In almost all cases the pure mean reversion strategy clearly outperformed the relevant 75% and 25% combined strategies; the returns generated by the optimised pure-mean reversion strategy portfolios were greater than those generated by the optimised combined strategy portfolios, and the lower confidence limit associated with these peak returns were larger.

The only notable exception was the 30-share combined P/E loser/value portfolio which generated a larger excess return (7.1% vs. 6.3%) and a lower standard deviation (13.9% vs. 20.0%) than its equivalent relevant 30-share pure mean reversion loser portfolio.

4.4.5 Hypothesis 3 conclusions

The hypothesis tested in this section was as follows:

H_0: The incorporation of P/E or B/M value measures into an optimised a mean reversion trading strategy will not improve that strategy.

H_a: The incorporation of P/E or B/M value measures into an optimised a mean reversion trading strategy will improve that strategy

Visual inspection of the surfaces created by the combined trading strategies suggested that, in most cases, the addition of a P/E or B/M eligibility criteria to a pure mean reversion trading strategy flattened the resulting surfaces of excess returns. (The 25% combined B/M loser/value strategy was the only exception).

Likewise, the proportion positive tests and difference-in-mean tests revealed a few instances where the combined trading strategy outperformed the pure mean reversion trading strategies. Unfortunately, as these tests explored not only the optimal portfolios but the surface as a whole, the resulting evidence cannot be used to reject the null hypothesis.

Finally, analysis of sample returns for optimal portfolios revealed the pure mean reversion portfolios to outperform the combined trading strategy portfolios in almost every single instance. The one exception noted (was the 30-share combined P/E loser/value portfolio) was not meaningful enough to allow us to

conclude that the combined P/E loser/value portfolio could outperform the pure mean reversion portfolio.

Therefore, after failing to find evidence to the contrary we must accept the null hypothesis and conclude that the incorporation of P/E or B/M value measures into an optimised a mean reversion trading strategy will not improve that strategy.

4.5 Summary of the results

The surface plots provided strong visual evidence of general trends that could be exploited by an investor to generate substantial market-beating returns; in almost all cases the surfaces exhibited reasonably smooth, sufficiently large areas of positive excess returns. Portfolio size, formation period (where applicable) and to a slightly lesser extent holding period, were shown to be effective drivers for optimising portfolio excess returns.

Optimised winner and loser mean reversion strategies were both shown to be effective in generating positive excess returns, however, the research proposition was not supported in that annualised returns generated by the optimised winner portfolios were greater than those generated by the optimised loser portfolios, particularly when spurious spikes in returns were excluded.

Optimised P/E and B/M growth and value strategies were also all shown to be effective in generating market beating returns. Modifying the strategies by scaling the value measures by their industry medians improved the two growth strategies, but worsened the two value strategies. In terms of points of maximum stable returns:

- The B/M growth strategy outperformed the P/E growth strategy, and both of these strategies were outperformed by the mean reversion winner strategy.
- The B/M value strategy, the P/E value strategy and the mean reversion loser strategy performed similarly well.

Ultimately the research yielded sufficient evidence to reject the first two null hypotheses, but the evidence was insufficient to reject the third. The conclusions of this research are therefore:

1. A trading strategy that exploits mean reversion of share prices could be used to create a portfolio that outperforms the market;
2. A value investing trading strategy could be used to create a portfolio that outperforms the market; and
3. The incorporation of value investing principles into a mean reversion trading strategy could not result in a trading strategy that outperforms a pure mean reversion trading strategy.

CHAPTER 5: CONCLUSIONS AND RECOMMENDATIONS

5.1 Introduction

This chapter contains the conclusions and recommendations pertaining to this study. It begins by summarising and attempting to offer explanations for key observations. Results are compared to those obtained in prior research. General observations that were applicable to all trading strategies are discussed and interpreted first, followed by observations specific to each of the three research hypotheses. Opportunities for further research are then proposed. The chapter closes with a summary of both the research conclusions and practical recommendations relevant to investors wishing to use this research to create a profitable trading strategy.

5.2 Interpretation of Results and Recommendations

5.2.1 General observations

In all cases, optimised trading strategies exhibited meaningful areas of sizable excess returns. This result casts doubts on the assumption of investor rationality. In agreement with Appiah-Kusi and Menyahs' (2003) findings regarding market efficiency of the JSE, the fact that it was possible for the optimised winner and loser portfolios to earn abnormal returns using share price trading rules suggests that the JSE is not weak-form efficient, at least in the short term.

Several themes were prevalent across all the surfaces of excess returns that were generated in this study:

Firstly, for short holding periods, the surfaces tended to exhibit large, irregular spikes and dips in returns. Over longer holding periods, the surfaces all tended to be generally smooth and reasonably well auto-correlated. Intuitively this makes sense because even though large daily share price movements do

sometimes occur, they are generally not cumulative, so over time they tend to cancel each other out in favour of an overall trend. Another way of thinking about it is that any single large movement in share price will be less significant over a longer holding period when the contribution that this movement makes to the overall annualised return is smaller. Statistically, if one were to think of daily share prices as individual trials, according to the central limit theory, the longer the holding period (i.e. the more trials conducted), the closer the average of the trials will be to the expected value.

Secondly, most of the surfaces exhibited seemingly regular corrugations. Though the corrugations sometimes ran in both directions, they were deeper and more prevalent across formation periods. The corrugations were mostly likely the result of the inherent randomness in the research design; for a given formation period the set of test portfolios (remember there are 30 of them) may perform better in relation to the market than those created using the adjacent formation period, and this better performance carries through for all holding periods, resulting in the corrugations. As one would expect, the corrugations tended to flatten out as portfolio sizes increased (the rationale for this expectation is the same as that used to explain the previous observation). It may also be worth noting that the corrugations in this study were more noticeable than those observed by Muller (1999), the reason being that the optimisation process in this research employed twice as many formation and holding period steps (each step being 35 days instead of 70 days).

Thirdly, as the portfolio size increased, excess returns tended to approach zero and risk (in terms of standard deviations of these excess returns) decreased. The reason for this is simply that larger portfolios included a greater proportion of the shares that make up the total market, so they were less likely to outperform the market and their returns more closely resembled market returns.

Lastly, larger excess returns tended to have larger standard deviations. This means that large returns tended to be driven by a few extremely high performing shares and/or portfolios (as opposed to all the portfolios and/or shares in the sample performing similarly well).

It is important that an investor employing any of the trading strategies in this research understands the above four tendencies. Such an investor would need to use this understanding to select portfolio parameters that balance the returns that he can expect to receive with the level of risk that he is willing to accept. Using the third point as an example, an investor should choose the smallest portfolio size that provides acceptable benefits of diversification – based on the research results this number seems to be in the region of 30 shares for all trading strategies tested.

Given the shortcomings of the statistical methods employed in this research, instead of relying on the statistics to choose portfolio parameters, an investor would be far better served by inspecting the charts visually and choosing a point of stable returns on the relevant surface. Such an approach would reduce the likelihood of the chosen trading strategy being unsuccessful due to the optimal portfolio parameters shifting over time.

Finally, in choosing a trading strategy, an investor would need to consider the difference between absolute and annualised expected returns. For the sake of simplicity, the approach consciously taken in this research was to compare portfolios based on their annualised excess returns. This approach may, however, not result in optimal choices when employed in practice. This is because the annualised returns generated by portfolios with shorter holding periods are generated by smaller absolute returns which will be eroded more quickly by transaction costs: these portfolios will require more frequent sales of shares and subsequent reinvestments than portfolios with longer holding periods. Using this logic, it may be in an investor's interest to sacrifice some of the expected annual returns in favour of a position on the surface with a longer holding period.

5.2.2 Discussion pertaining to Hypothesis 1

In regards to Hypothesis 1, the evidence presented in section 4.2. was sufficient to reject the null hypothesis, and conclude that an optimised mean reversion trading strategy will outperform the market. The remainder of this section expands on this conclusion.

In section 3.2 is was proposed that:

i. The optimised winner portfolio would outperform the market, and

ii. The optimised loser portfolio would outperform the optimised winner portfolio.

When points of unstable return were excluded, the research revealed that the optimised winner portfolio (a 30-share portfolio with a formation period of 165 days and a holding period of 60 days) outperformed the market by an average of 18.5%, while the optimised loser portfolio (a 30-share portfolio with a formation period of 1,355 days and a holding period of 165 days) only outperformed the market by 6.3%. Therefore, while both the optimised winner and loser portfolios were shown to have outperformed the market, the optimised loser portfolio did not outperform the optimised winner portfolio.

The finding that the optimised winner portfolio did not outperform the optimised lower portfolio is in conflict with Muller's (1999) research[2]. Muller's equivalent winner portfolio (a 30-share portfolio with a formation period of 340 days and a holding period of 60 days) outperformed the market by 14.3%, and his equivalent loser portfolio (a 30-share portfolio with a formation period of 900 days and a holding period of 340 days) outperformed the market by 17.4%.

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[2] It should be noted that this research did not exactly replicate that of Muller (1999). For example, Muller ignored the portion of the returns that an investor would have received as dividend payouts. Nevertheless, the differences across the results of the two studies are pronounced enough to be worth noting.

The results shed some insight into the persistence of the mean reversion effect and the stability of optimal portfolio parameters over time. The differences between the results of this research and Muller's (1999) study suggest that, though the trading strategies still seem to be able to generate significant market-beating returns and optimal holding and formation periods were broadly in line with those witnessed previously, the arbitrage opportunities available to an investor may be lessening over time. In the case of winner portfolios, the lower optimal formation period (165 days vs. 340 days) suggests that investor overreaction while share prices are on the increase is not as long lived as it used to be. In the case of loser portfolios, the returns generated by the loser strategy have noticeable lessened (from 17.4% to 6.3%).

Unfortunately, as there are only two sets of results to compare, it is not possible to ascertain whether the observed reduction in arbitrage opportunities over time is temporary or on-going. To illustrate the point, consider how investor behaviour might change in a bull market: because the market as a whole is strong, investors might become more confident that poorly performing shares would recover quickly, so they would tend to overreact less to falling share prices, and in doing so cause a loser strategy to perform poorly. Such optimistic behaviour would less likely should there be a crash in the market. (As can be seen in Figure 3, for several years prior to the crash of 2008, the JSE was very strong).

Though the evidence provided in this study is insufficient to allow for any definitive conclusions regarding the persistence of the mean reversion effect and the stability of optimal portfolio parameters over time, the data do seem to support Chen and Sauers' (1997) conclusion that overreaction isn't consistent over time. As the optimised portfolios did generate market bearing returns, there is insufficient evidence to confirm Bartens & Hassans' (2010) conclusion that momentum strategies on the JSE do not always outperform the market.

A second difference worth mentioning between these results and those of Muller's (1999) research is the significance of the formation period, particularly with respect to the winner strategy; this research found the formation period to be a powerful driver of excess market returns while Muller's did not. In this

author's opinion, the formation period being a more powerful predictor meant that the shapes of the winner surfaces in this research were more consistent with what mean reversion theory would have predicted, because they showed winner excess returns to be relatively short lived. The relatively short window in which in which an investor could have capitalised on the mean reversion effect would have meant that increasing either the formation period or the holding period would have resulted in lower excess returns – as it turns out this effect can clearly be seen in the winner surfaces (see Figure 5 as an example). Furthermore, as either the formation period or holding period increased past a certain threshold, excess returns became negative as investors began overreacting in the opposite direction.

The shapes of the loser surfaced in this research are also consistent with what mean reversion theory would have predicted. The band of positive excess returns that occurred diagonally across the loser surfaces (see Figure 8 as an example) implied that an investor could have changed his portfolio's holding period and still benefited from the constituent shares' reversions to their means, provided he also changed his portfolios formation periods in the opposite direction at the same time. (It may be useful to refer to Figure 2 when visualising why this should be the case). Continuing to use the 30-share loser surface in Figure 8 as an example, a portfolio with a formation period of 900 days and a holding period of 690 days yielded a similar return to a portfolio with a formation period of 795 days and a holding period of 760 days.

5.2.3 Discussion pertaining to Hypothesis 2

The results of the empirical tests showed that optimised P/E and B/M growth and value strategies were all able to generate market-beating returns. In terms of points of maximum stable returns, and prior to the addition of industry scaling, the P/E growth and value strategies yielded annual excess returns of 2.7% and 5.2% respectively, while B/M growth and value strategies yielded annual excess returns of 11.2% and 6.2% respectively. Given this evidence is was possible to reject the null hypothesis pertaining to Hypothesis 2, and

conclude that an optimised value strategy that exploits the P/E effect or the B/M effect will outperform the market.

Furthermore, it was shown that for both P/E and B/M strategies the application of industry scaling improved the growth strategies, but decreased the effectiveness of the value strategies. This result is interesting because of the asymmetry in investor behaviour that it implies; it would seem that in order to determine whether shares are expensive in terms their P/E or B/M values, investors benchmark these values against the P/Es and B/Ms of other shares in the same industry, but to determine when shares are cheap, they simply compare the values to the market as a whole. Such as distinction is not rational, and seems to fall within the ambit of behavioural finance (but is not explained by any behavioural finance effect that the author is aware of).

In agreement with prior research performed on the JSE (Auret & Sinclaire, 2006; Basiewicz & Auret, 2010), the B/M ratio was found to be a more powerful predictor of future results than that P/E ratio. In all cases (both with and without the application of industry scaling), the B/M strategies generated larger excess returns at their peaks of stable return than their equivalent P/E strategies (though this differences were far more notable across the growth strategies).

In seeming conflict with Mutooni and Mullers' (2007) research, mean reversion strategies were found to be more effective in generating excess returns than the value and growth style strategies. After the application of industry scaling, the optimised P/E and B/M growth strategies yielded excess returns of 6.1% and 12.9%, compared to the winner strategy's 18.5%. The differences were far smaller in the case of the value strategies (5.2% and 6.2% vs. the loser strategy's 6.3%).

Another dissimilarity between the mean reversion and P/E and B/M strategies related to the effect of portfolio size; while the winner and loser strategies yielded positive (though admittedly steadily decreasing) returns over a very wide range of portfolio sizes, the P/E and B/M strategies displayed very little success for portfolio sizes smaller than 20 shares or larger than 40 shares.

Finally, the shapes of the P/E and B/M surfaces (excluding the B/M growth surface) suggest that the trading strategies that generated these surfaces might easily be improved by modifying these strategies slightly. Excess returns on these surfaces were negative for portfolio sizes of less than approximately 10 shares. This means that the first few shares contributed negatively to the portfolios' excess returns. Therefore, if one were to change the strategies to automatically exclude those first few shares, the optimised portfolios' excess returns would be larger.

5.2.3 Discussion pertaining to Hypothesis 3

The research was unsuccessful in finding a way to improve the mean reversion trading strategies by incorporating P/E or B/M constraints into the strategy. Instead of increasing the excess returns generated by the test portfolios, the addition of the constraints had the effect of flattening the surfaces. Imposing severe restrictions (i.e. using the 25% combined strategies) had the effect of making the surfaces resemble those created by the pure P/E and B/M strategies which, as explained in the previous section, hadn't outperformed the pure mean reversion strategy either. The lack of evidence to the contrary meant that it was not possible to reject the null hypothesis pertaining to Hypothesis 3, so it was therefore concluded that the incorporation of P/E or B/M value measures into an optimised a mean reversion trading strategy will not improve that strategy.

This finding confirms the work done by Frasier and Page (1999). Even though they found that momentum and value strategies on the JSE had the power to independently predict future returns, they were unable to find evidence of interaction between value and momentum effects.

That said, the very fact that the combined strategies in this research performed worse than the pure mean reversion strategies suggests that one may be able to create a more effective combined trading strategy (based on the mean reversion and P/E or B/M effects) than the combined trading strategies tested in this research. The supposition tested by combined trading strategies in this research was that one would be able to "weed out" the shares in the mean

reversion loser (or winner) portfolios that would not perform well over the subsequent holding period, by excluding the shares whose P/E or B/M ratios suggested that, even though these shares had performed poorly (or well) over the formation period, these shares were still over (or under) priced. The fact that the P/E and B/M exclusion criteria flattened the surfaces of excess returns, implies that at least some of the shares excluded by these criteria would have outperformed the market over the holding period. In other words, it means that the set of shares that beat the market when using the mean reversion loser (or winner) strategy, was not exactly the same as the set of shares that beat the market when using the P/E or B/M value (or growth) strategies (but probably overlapped). Therefore, if one had to employ a combined trading strategy that successfully selected a portfolio comprising:

a) the shares that beat the market when using the mean reversion loser (or winner) strategy, *and*
b) the shares that beat the market when using the P/E or B/M value (or growth) strategies,

such a strategy may have outperformed the combined trading strategies tested in this research. If one had managed to do the above while not introducing any additional non-performers into the portfolio, mathematically such a strategy would definitely have outperformed the combined trading strategies tested in this research, and may have even outperformed the pure mean reversion strategies too.

The potential for a such a combined trading strategy to outperform the pure mean reversion strategies is supported by the work done by Muller and Ward (2012). (As explained in section 2.4.3, Muller and Ward used a weighted average type approach to construct a combination equity style, starting with the best performing style, and systematically adding styles which contributed the greatest improvement to the result. Their best performing combination style, which included momentum and earnings yield, consistently outperformed the market by about 14% per annum).

The observed lack of interaction between the mean reversion and growth and value effects may go some way to explaining the persistence of the mean reversion effect. One would expect the fact that investors are aware of the existence of mean reversion to lead to the erosion of arbitrage opportunities as more and more investors follow trading strategies designed to exploit the mean reversion effect. However, one must consider that an investor selecting a share based on mean reversion would need to completely ignore other factors such as that share's P/E or B/M ration in order to reap the full benefit of the effect. Psychologically this would be difficult to do if, for example, these ratios suggested that a share identified by the trading rules was already overpriced. The investor would be tempted to skip over the share in question and instead move onto the next. Investors acting in this was would never capitalise fully on the mean reversion arbitrage opportunities, so the effect would persist (though perhaps as a slightly watered down version of its prior self).

5.3 Suggestions for Further Research

5.3.1 Refine the growth and value strategies

As explained in section 5.2.3, the P/E and B/M growth and value surfaces (excluding the B/M growth surface) exhibited negative excess returns for small portfolio sizes of less than approximately 10 shares, and mathematically this implies that excluding one or more of those first few shares from the test portfolios would have improved the optimised portfolio's performance. Further research could attempt to improve the P/E strategies by finding a way to exclude these poor performing shares from the growth and value portfolios.

5.3.2 Inclusive combined strategy

In section 5.2.4 it was explained how an inclusive combined strategy that successfully managed to select the "best" mean reversion shares and the "best" P/E or B/M shares would have outperformed the combined strategies tested in this research. Identifying such a strategy is therefore recommended as a topic for future research.

One approach to test whether such an inclusive combined strategy would generate market-beating returns would be to follow an optimisation process like one used in this research, but modified as follows:

- The P/E and B/M exclusion criteria would be removed.
- The combined test portfolio would be made up of the top X shares from the mean reversion winner (or loser) portfolio and the top Y shares from the P/E or B/M growth (or value) portfolio.
- The test portfolio would be optimised in terms of holding period, formation period, X and Y, with portfolio return as the dependant variable. (It would not be necessary to optimised on portfolio size because portfolio size = X + Y).

5.3.3 Adjusting for risk

As explained in the literature review in chapter 2, it is frequently suggested that the abnormal returns resulting from the mean reversion, P/E and B/M equity effects are a result of the high performing shares bear higher fundamental risk of some sort, and that their higher average returns are simply compensation for this risk. Therefore further research into the optimisation of risk adjusted portfolios that exploit the mean reversion, P/E and/or B/M effects would add greatly to this research and be considerably useful to investors' wishing to employ trading strategies such as or based on those tested in this study.

5.3.4 Trading costs

An investor attempting to implement a real-life trading strategy based on the trading strategies tested in this research would need to consider the effect that trading costs, such as brokerage fees and taxes, would have on expected returns. Furthermore, as trading costs erode a greater portion of the annual returns for shorter holding periods, a better understanding of these costs would allow an investor to make sounder decisions regarding optimal portfolio parameters (i.e. preferred points on the surfaces of excess returns). Therefore it would be beneficial to investigate the effectiveness of trading strategies that

exploit the mean reversion, P/E and/or B/M effects when trading costs are considered.

5.3.4 Optimal portfolio parameters and excess returns over time

In section 5.2.2 it was explained how the differences between the results of this research and that of Muller's (1999) may indicate that both the opportunities to generate excess returns using mean reversion strategies and the optimal portfolio parameters to do this are changing over time, but that the current evidence did not allow for any confident conclusions. From an investor's perspective, understanding the predictability of optimal portfolio parameters and expected excess returns is essential, as this knowledge had direct implications in term of the investor being able to employ these trading strategies successfully in a real-world scenario. Improving these understandings is therefore recommended as a topic of future research.

5.4 Conclusion

The research set out to identify commercially exploitable arbitrage opportunities, based on the theories of mean reversion, value investing and a combination of these theories, that could be used by an investor to earn market-beating returns on the JSE.

The results of the portfolio optimisation simulations revealed significant opportunities for market outperformance. All optimised trading strategies exhibited meaningful areas of substantial excess returns. Optimised loser portfolios outperformed optimised loser portfolios, and both of these outperformed their associated P/E and B/M value and growth strategies. Incorporating P/E or B/M constraints into the mean reversion strategies proved to reduce the effectiveness of those mean reversion strategies.

An investor attempting to employ any of these trading strategies should not rely only on the statistics, but should also visually inspect surfaces of excess returns to select portfolio parameters that suit his or her risk appetite. Large areas of stable excess returns are preferable, but selecting points on these areas (as

opposed to selecting points on rough areas of the surfaces of excess returns) typically requires the sacrifice of some expected returns in exchange for lower volatility of portfolio returns. Another reason why these stable positions are preferable is that an investor choosing such a position is less likely to suffer losses should optimal portfolio parameters shift over time.

In any event, in order to benefit from any of the trading strategies investigated in this research, an investor would need to have the nerve to follow the trading rules blindly and suspend judgement as they direct him to buy an often seemingly unspectacular bundle of shares and hold them for extended periods of time - if this were easy to do, the mean reversion and value effects would not be as persistent as they have proven to be.

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APPENDIX A

Test portfolio start dates:

	Bucket Start Date	Bucket End Date	Randomly Selected Start Date
1	2004-11-01	2004-12-19	2004-11-05
2	2004-12-19	2005-02-06	2005-01-06
3	2005-02-06	2005-03-27	2005-02-25
4	2005-03-27	2005-05-14	2005-04-19
5	2005-05-14	2005-07-02	2005-06-05
6	2005-07-02	2005-08-20	2005-08-05
7	2005-08-20	2005-10-07	2005-09-25
8	2005-10-07	2005-11-25	2005-11-12
9	2005-11-25	2006-01-13	2006-01-01
10	2006-01-13	2006-03-03	2006-01-14
11	2006-03-03	2006-04-20	2006-03-09
12	2006-04-20	2006-06-08	2006-05-30
13	2006-06-08	2006-07-27	2006-06-14
14	2006-07-27	2006-09-13	2006-09-07
15	2006-09-13	2006-11-01	2006-10-01
16	2006-11-01	2006-12-20	2006-11-30
17	2006-12-20	2007-02-06	2007-01-03
18	2007-02-06	2007-03-27	2007-02-16
19	2007-03-27	2007-05-15	2007-04-11
20	2007-05-15	2007-07-03	2007-06-14
21	2007-07-03	2007-08-20	2007-07-05
22	2007-08-20	2007-10-08	2007-09-10
23	2007-10-08	2007-11-26	2007-11-06
24	2007-11-26	2008-01-13	2007-12-01
25	2008-01-13	2008-03-02	2008-02-11
26	2008-03-02	2008-04-20	2008-04-17
27	2008-04-20	2008-06-07	2008-05-21
28	2008-06-07	2008-07-26	2008-07-25
29	2008-07-26	2008-09-13	2008-08-01
30	2008-09-13	2008-11-01	2008-09-16