The University of Sydney

Performance of Active Extension Strategies in the Australian Equities Market

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ABSTRACT

This dissertation examines the performance of active extension strategies, also known as ‘130/30’, in the Australian equities market. This strategy involves introducing short positions to 30% of the value of a fund while increasing the number of long positions to 130%, providing 100% net exposure to the market while giving the ability to take a larger number of active positions. A detailed analysis of the factors affecting performance is explored using a simulation approach based on eight years of historical returns for the constituents of the S&P/ASX 200 index and a variety of realistic cost assumptions. This study builds on previous analysis by using a simulation approach that allows a larger number of contributing factors to be analysed with greater precision. There is also a unique advantage to using active extension strategies in the Australian market, as a higher level of benchmark concentration relative to other major developed market indexes should lead to a higher performance increase from active extension strategies over traditional long-only portfolios. This is also one of the first analyses of this kind in the Australian market and should have a high degree of relevance to institutional investors considering active extension strategies.

This study finds a statistically significant increase in performance from active extension strategies over equivalent long-only portfolios, holding all other factors constant. This increase is greatest for managers with higher levels of skill, where the manager is equally skilled at picking long or short positions. The performance increase from active extension portfolios is greatest where any tracking error limit is high and costs are low. Volatility and cross-sectional dispersion of returns, two factors hypothesised in the literature to affect the relative advantage of active extension strategies, are found to have no discernable effect. Similarly, there is no measurable difference in relative performance in rising or falling markets. Overall, this study concludes that there is a performance gain in relaxing the long-only constraint, provided costs are low, any tracking error target is not extremely low, and the manager has a reasonable degree of skill in selecting stocks both long and short.

1. OVERVIEW

The long-only constraint is one of the most common and most binding portfolio constraints imposed on fund managers. Restricting short sales prevents managers from fully implementing their complete information set into their portfolio construction. Recently, a portfolio structure commonly known as '130/30' or 'active extension' has become common, as it relaxes the short-selling constraints associated with long-only portfolios while retaining an exposure to market returns that market neutral long-short portfolios do not have. In theory, relaxing the short-selling constraint on portfolio construction allows for the construction of more efficient portfolios that generate higher performance on a risk-adjusted basis. However, increasing short-selling also increases costs relating to turnover, stock borrow and financing which act as a drag on portfolio performance. Previous research focused on the US equities market has proposed that the increased performance of active extension portfolios outweigh the costs, leading to higher risk-adjusted performance. This research aims to verify that this proposition holds true for the Australian equities market under a number of realistic cost assumptions. Additionally, this research quantifies the sensitivity of performance to a number of endogenous and exogenous factors such as the level of manager skill, risk target, costs and benchmark characteristics.

This area of research has a high degree of relevance to institutional investors seeking guidance on the appropriate level of short-selling for a fund by quantifying the benefits of introducing short-selling to existing long-only Australian equity portfolios. The rapid growth in uptake of active extension strategies has made pertinent an examination of the performance of these strategies relative to traditional long-only strategies. Funds under management for active extension strategies has grown rapidly, climbing 77% over twelve months to US$53bn as of September 2007[1], with growth to over US$2 trillion forecast by 2010[2]. A large source of growth for active extension strategies is expected to come from pension funds, which currently account for ownership of 35% of global listed equities. 58% of US Defined Benefit funds are either using or seriously considering active extension strategies[3]. The most common level of short-selling associated with these funds is a fixed level of 30% (130/30), although as will be shown the most appropriate level of short selling varies depending on the characteristics of the relevant portfolio. Performing an examination into the potential performance of these strategies in the Australian equities market should assist investors who are considering these strategies over traditional long-only funds or market-neutral long-short funds. This study also provides an analysis of the magnitude to which active extension portfolios outperform long-only portfolios under a variety of market conditions and manager-specific variables that can assist investors who are considering whether to invest in active extension strategies.

As the uptake of active extension funds continues to grow rapidly, it is important to have a theoretical and empirical understanding of the performance of this portfolio structure. Although similar studies have been conducted by Sorensen, Hua and Qian (2007) as well as Armfelt and Somos (2008) on the US market, to date there has been no similar analysis performed on the Australian market. This study also builds on previous literature by testing both the effectiveness of active extension strategies and their sensitivity to various market and portfolio characteristics. The results of this study also build on previous hypotheses and empirical studies conducted predominantly in the

[1] Pension and Investments (2007)
[2] Tabb and Johnson (2007)
[3] Pyramis (2006)

US equities market, by showing there is a tangible benefit in introducing short-selling into long-only portfolios.

Active extension funds also have considerable appeal in the Australian market due to higher concentration in the S&P/ASX 200 benchmark, lower regulatory restrictions on the amount of leverage that can be employed in retail funds and a highly liquid market for borrowing stock. Although active extension portfolios are not yet as common in the Australian market as they are in Europe or the US, some Australian superannuation funds have followed the lead of pension funds in these markets in providing active extension strategies to investors. Given the lack of previous research directed towards the Australian market, there is considerable scope for academic research into quantifying the benefits of active extension strategies within the Australian equities market. Considering the growing uptake in active extension strategies by superannuation funds and other institutional investors, an analysis of the performance of active extension strategies is also of prime importance to these participants.

The remainder of this study is organised as follows. Chapter 2 provides an introduction to the theoretical basis for active extension strategies, as well as the benefits and costs of relaxing the short-sale constraint. Chapter 3 outlines the securities regulation that applies to active extension funds and gives an overview of existing active extension funds in the Australian equities market. Chapter 4 reviews the theoretical and empirical studies that have been conducted on the performance of active extension strategies. This is followed by Chapter 5 with a description of the hypotheses to be tested. Chapter 6 describes the data to be tested as well as providing an explanation and justification of the model used. Chapter 7 provides results and Chapter 8 presents conclusions.

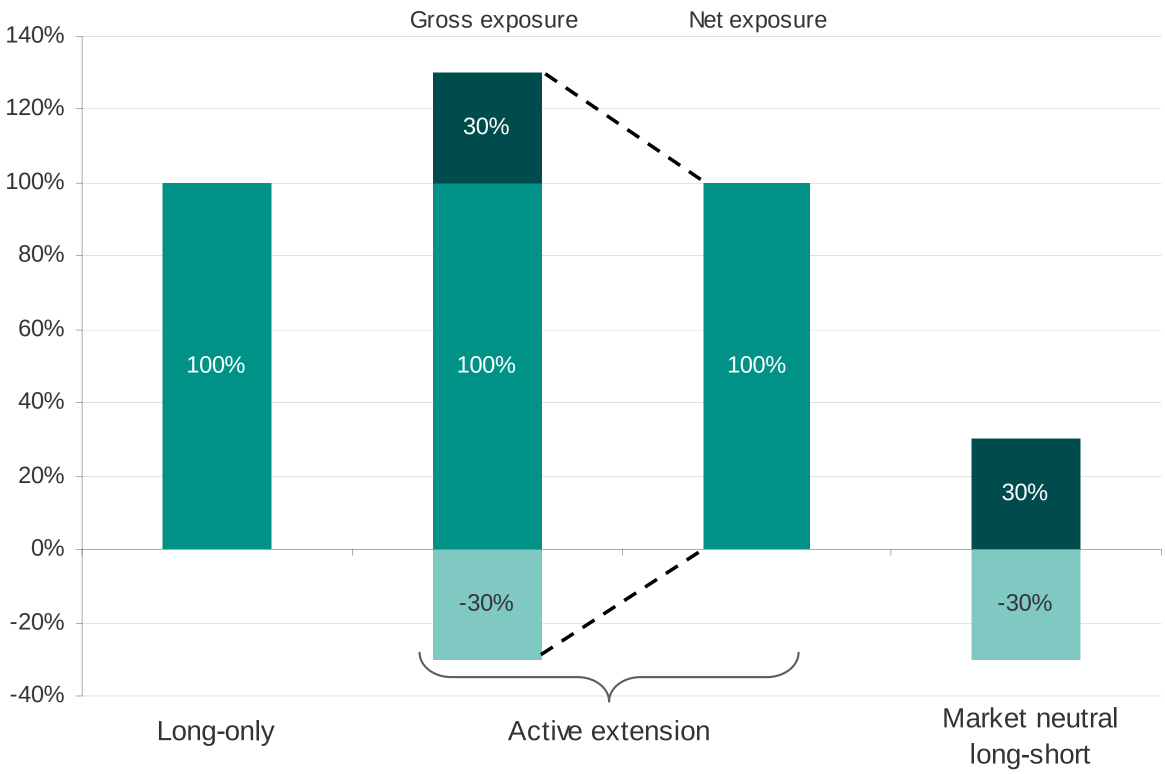
2. THEORETICAL BACKGROUND

2.1 Overview of active extension strategies

In recent years, a portfolio structure known as '130/30' or 'active extension' has become increasingly common. In this type of portfolio, securities to 30% of the value of the fund are short-sold, with the sale proceeds reinvested into the long side of the portfolio. On a net basis the portfolio has a 100% exposure to the market and often has a target beta of one. This portfolio structure presents a hybrid of the market exposure that traditional long-only portfolios have with the ability of a long-short fund to take short positions. Although the name '130/30' is commonly used to describe this portfolio structure, it is often used as a generic term for active extension portfolios with different amounts of leverage. As the '130/30' label suggests, a short-selling level of 30% is most commonly used for these strategies, although there is nothing to suggest that this represents an optimal level of short-selling. In practice, the optimal level can vary depending on factors including the level of manager skill, risk target, costs and benchmark characteristics. A level of 30% may represent overgearing or undergearing depending on these factors, leading to the construction of an inefficient portfolio.

Proponents of this type of strategy argue that it combines the advantages of the exposure to market returns of a long-only portfolio with the ability of a long-short market-neutral portfolio to take short positions. The structure of an active extension portfolio relative to similar equity portfolios is shown in Figure 2.1. Unlike a long-short portfolio style traditionally adopted by hedge funds, the fund is fully invested in the market at all times and does not seek to generate excess returns by market timing.

Figure 2.1: Comparison of active strategies



Instead, the benefit of the strategy comes from removing the long-only constraint and introducing the ability to short-sell stocks. Active extension strategies are typically benchmarked to an equity index to reflect their full exposure to the market, unlike traditional market neutral long-short strategies which are often measured against a total return benchmark such as the cash rate. By relaxing the long-only constraint, managers are able to fully utilise their views on stocks they expect to underperform as well as taking additional positions in stocks they expect to outperform.

Although active extension funds are sometimes viewed as a type of hedge fund strategy due to the short-selling employed, in practice they have greater similarities to traditional long-only equity portfolios with the addition of greater flexibility and efficiency. Most active extension funds have mandates to take positions in equities only and do not invest in the wide range of assets that some hedge funds invest in. Active extension strategies have return characteristics that are closer to long-only funds than market-neutral funds, as they have 100% net exposure to equities at all times and are typically benchmarked to a market index. However, similarities exist between the fee structures seen in active extension funds and hedge funds. Active extension funds, like hedge funds, often charge a performance fee in addition to a base fee that is typically higher than that charged by long-only funds. Table 2.1 highlights the key differences between active extension strategies, long-only portfolios and long-short hedge funds.

Table 2.1: Overview of similar equity active management strategies

	Long-only	**Active extension**	**Market Neutral Long-Short**
Investment style	Relative return	Relative return	Absolute return
Benchmark	Market index	Market index	Cash rate/hurdle rate
Net exposure	100%	100%	0%
Gross exposure	100%	160%[4]	Variable
Target beta	1	1	0
Short selling	None	30%[4]	Variable
FUM	US$63.7t[5]	US$53.3b[2]	US$2.48t[5]
Typical management fee	30-80bp[5]	60-150bp[5]	>150bp[5]
Performance fee	Usually 0%	0-20%	Typically 20%
Introduced in:	Mid-1800s	Late 1990s	1949

2.2 Benefits of active extension strategies

The prime benefit from relaxing the short-sale constraint comes from the ability to take full advantage of negative information about a security. When the constraint on short-selling is imposed, managers are restricted from efficiently implementing their sell ideas into the portfolio. In the absence of short-selling, the minimum position that can be

[4] Assuming typical 130/30 structure
[5] Collins (2007)

taken in a security is to have a zero holding. Relative to the index position, the maximum underweight position that can be taken in terms of active weighting is the negative of the index weight. Relaxing the long-only constraint improves the ability of a manager to implement their negative views on a stock by increasing their potential to take larger underweight positions to benefit from stocks they expect to underperform. Additionally, the extra 30% in long positions allows the manager to gain greater exposure to stocks they expect to outperform by taking greater overweight positions.

An additional advantage is based on an argument originally put forward by Miller (1977) is that there are inefficiencies that exist on the short side of the market due to the prevalence of the long-only constraint. Artificial restrictions placed on long-only funds by constraints on short selling have the potential for stocks to become overvalued, leading to market inefficiencies. This implies that active extension managers may be able to exploit short-side inefficiencies that long-only managers are unable to take advantage of. Grinold and Kahn (2000a) propose that it is difficult to show these inefficiencies can be exploited by short sellers in reality due to the high implementation costs required. In any case, the critical difference with active extension strategies is the relaxation of the constraint on active underweight positions that exists in long-only funds.

The benefits from relaxing the short-sale constraints are highly related to the level of benchmark concentration. Benchmark concentration refers to the large proportion of an index made up of a small number of stocks with large market capitalisations. For example, the largest 12 stocks in the S&P/ASX 200 index represent 50% of the benchmark by capitalisation, with the remaining 189 stocks comprising the remaining

50%.[6] Only the largest 21 stocks in the index have an index weight above 1%, with the bottom 180 having benchmark weights below 1%.[7] In a long-only context, it is difficult to achieve a meaningful underweight position in these stocks with a restriction on short-selling in place. Foley (2006) quotes the impact of the uneven distribution of benchmark weights as an important motivation for active extension strategies. Where benchmarks are more highly concentrated in a small number of large-cap stocks, the tail of smaller stocks have lower weightings in the index. As the long-only constraint effectively restricts the underweight position on a stock to the negative of its index weight, the ability of a manager to implement a meaningful underweight position is restricted. This characteristic of concentrated benchmarks reduces the ability of managers to implement their negative views evenly across larger and smaller stocks in the benchmark without the ability to sell short, restricting a manager's ability to construct efficient portfolios.

Figure 2.2 shows the distribution of index weights in the S&P/ASX 200 ranked from largest to smallest along the horizontal axis. By displaying the index weights in this manner, it shows that there are a small number of large stocks and a long tail of relatively smaller stocks in the index. Similar analysis by Martelli (2005) based on the S&P 500 composition in 2003 found that a long-only manager can only underweight 88 of 500 stocks at a greater level than 0.25%. Table 2.2 shows the six largest and six smallest stocks in the S&P/ASX 200 and their respective index weights. The maximum underweight position under the long-only constraint gives the most scope for underweighting in larger stocks, however for the smaller stocks in the index the maximum underweight position without short-selling is an insignificant 0.02%.

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[6] Bloomberg, as of 2 May 2008

[7] There were 201 stocks in the S&P/ASX 200 index as of 2 May 2008.

Figure 2.2: S&P/ASX 200 index concentration

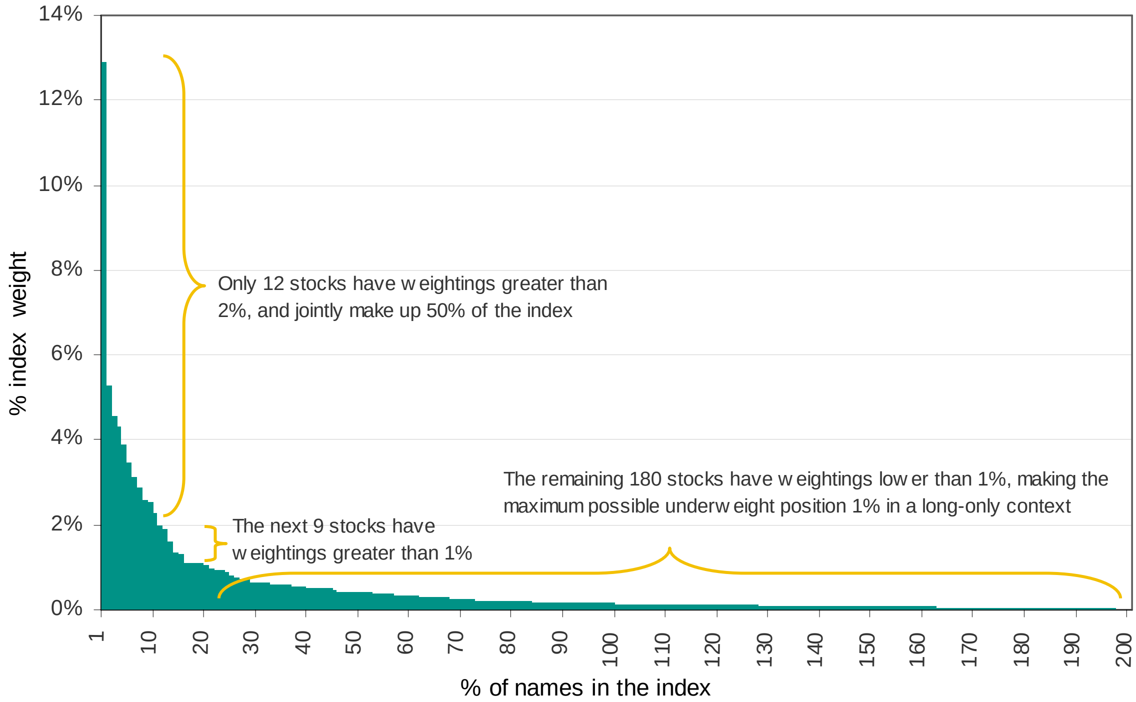


Figure 2.3: Cumulative benchmark concentration of comparable indexes

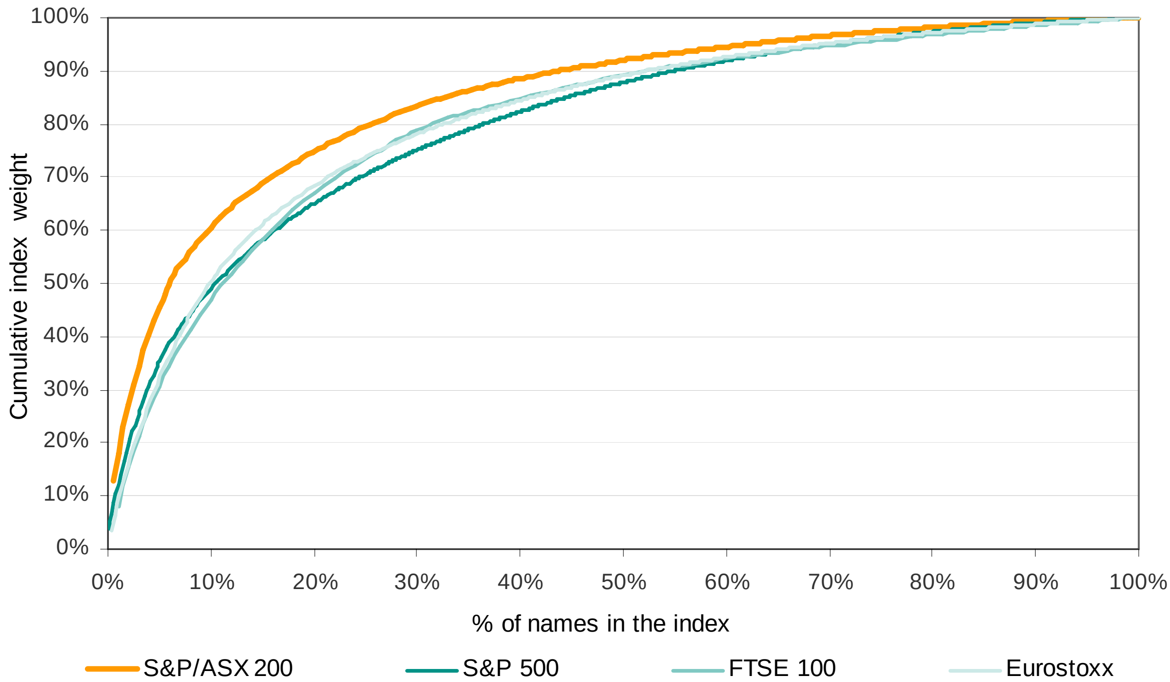


Table 2.2: Largest and smallest S&P/ASX 200 weightings

Name	Index Rank	Index Weight[8]	Max underweight with short-selling constraint
BHP Billiton	1	12.91%	-12.91%
Commonwealth Bank	2	5.28%	-5.28%
National Australia Bank	3	4.56%	-4.56%
Westpac Banking Corp	4	4.29%	-4.29%
ANZ Banking Group	5	3.88%	-3.88%
Rio Tinto	6	3.46%	-3.46%
Octaviar Ltd	196	0.03%	-0.03%
AED Oil Ltd	197	0.02%	-0.02%
APN Property Group	198	0.02%	-0.02%
TSI Fund	199	0.02%	-0.02%
Allco Finance Group	200	0.02%	-0.02%
Perilya Ltd	201	0.02%	-0.02%

Table 2.3: S&P/ASX 200 distribution by size

	>3.0%	1.0-3.0%	0.5-1.0%	0.1-0.5%	0.01-0.1%
N	7	14	23	90	67
% of ASX 200	37.5%	24.0%	15.3%	19.3%	3.9%

Benchmark concentration in the Australian market is more pronounced than that in other developed markets due in part to the large weighting of BHP Billiton, Rio Tinto, Woolworths and the four major banks. Figure 2.3 shows a Lorenz curve, which depicts a higher cumulative index weighting of the S&P/ASX 200 index compared to other major developed market indexes as of 2 May 2008. Applying the metric of benchmark concentration[9] used by Grinold and Kahn (2000a) benchmark to the S&P/ASX 200 gives a value of 0.85, compared to 0.80 for the S&P 500, 0.81 for the FTSE 100 and

[8] S&P/ASX 200, as of 2 May 2008

[9] The measure of benchmark concentration used by Grinold and Kahn (2000a) is the Gini coefficient applied to cumulative index weights, which is measured as twice the area under the cumulative weight curve in Figure 2.3 minus that of an equal-weight benchmark.

0.81 for the Eurostoxx 300, suggesting that the Australian market has a higher degree of benchmark concentration relative to other major indexes of developed markets. Consequently, the ability to underweight most stocks in the Australian market without the use of short selling is lower. In the Australian market, this should provide a greater benefit to managers in relaxing the long-only constraint in their portfolios.

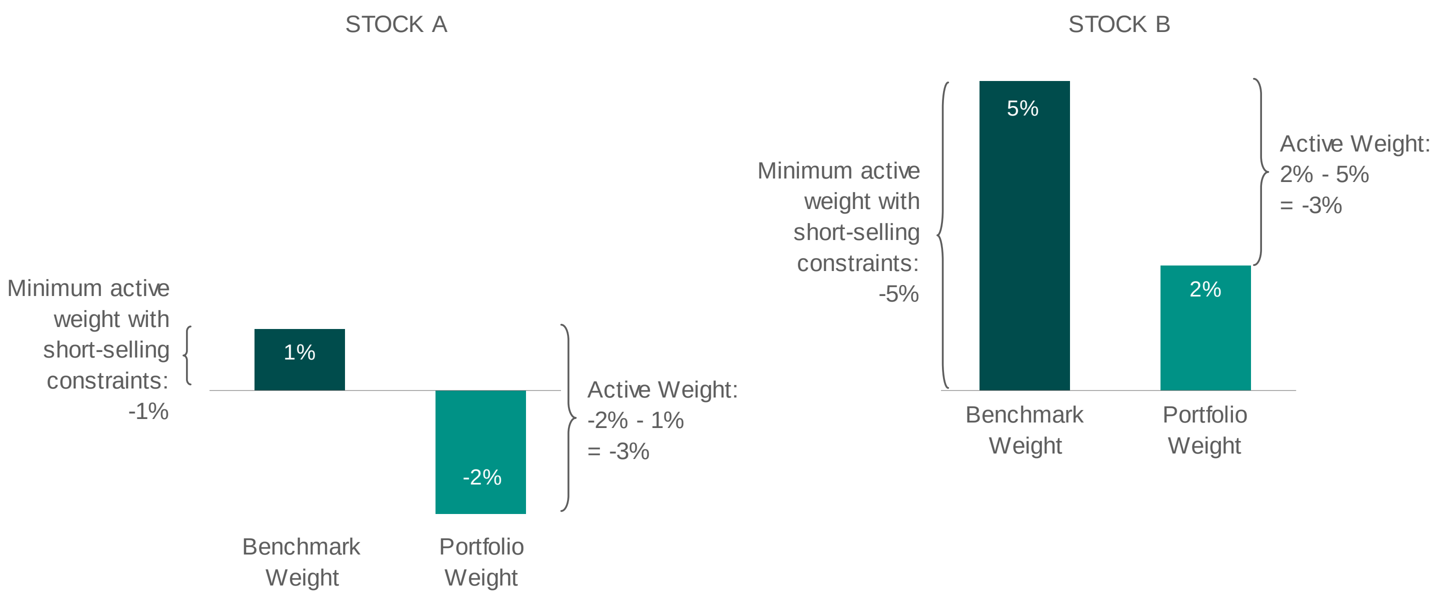
An argument put forth by some is that active extension portfolios are inherently more risky than long-only portfolios because of their higher gross exposure (Patterson, 2006). Although increasing the gross exposure of the fund by adding extra short-side and long-side positions to a portfolio would intuitively appear to increase risk, this is not necessarily the case. An active extension portfolio can be constructed with the same level of risk as a long-only portfolio using the same set of forecast returns, and as will be shown, should on average lead to a higher risk-adjusted return before costs. Since increasing the level of short positions also involves adding an equal amount of long positions, the systematic risk from the extra short positions are offset. The increased residual risk can be mitigated in the construction of the portfolio by proportionally reducing the size of other active positions. The ability to utilise short-side information in the active extension portfolio should allow for an increased level of performance with the same level of risk, as measured by tracking error. [10]

An alternative approach to examining the added risk of active extension portfolios is to examine the portfolio's holdings in terms of active weights. Active weights are defined as the portfolio weight in a security less the benchmark weight, and provide a measure

[10] Tracking error refers to the standard deviation of portfolio returns against the benchmark return. In this context, risk refers to the deviation of the portfolio returns from the benchmark returns. The use of tracking error as a measure of portfolio risk is common through industry and in the active management literature (see Grinold and Kahn, 2000).

of portfolio weighting relative to a benchmark. With the long-only constraint in place, the smallest position possible in an individual stock is 0%, and hence the lowest active weight possible to have in a single stock is the negative of its benchmark index weight. Figure 2.4 gives an example of two stocks with equal active weights but different index weights and demonstrates that for a long-only portfolio, negative active weightings are easier to achieve for stocks with a large weighting in the benchmark index:

Figure 2.4 – Identical active weights on different sized stocks



The limitation of restricting the size of active underweight positions to the index weights acts as a restriction on the ability of a manager to fully implement stocks they consider 'sells' into their portfolios. The sum of individual stock returns multiplied by their active weight in the portfolio gives the portfolio's active return, or portfolio performance less benchmark performance. The marginal contribution of a position in a stock to portfolio outperformance can be measured by its active weight multiplied by active return, with the sum of these contributions equalling the portfolio's active return. For example, if Stock B in figure 2.4 has a -10% performance and a -3% active weight, the individual contribution of that position to the portfolio's active return is 0.3%. Thus in terms of contribution to active returns, a portfolio weight in stock A of -2.5% (active weight of -3%) is equivalent to a portfolio weight of 2% in stock B (active weight of -3%). As the short-selling constraint restricts managers from taking active positions below the negative of the index weight, this severely curtails the size of the underweight positions that can be taken in smaller stocks. Thus for the 131 stocks with index weights below 0.25%, managers are effectively limited to act on positive information on security returns and have a severe restriction on their ability to act on downside information.

As tracking error is defined as the deviation of portfolio active returns, the marginal risk contribution of an active position is related to its active weight and not whether shorting is required to achieve that active weight. In terms of tracking error, the standard deviation of portfolio active returns, if it is assumed that both stocks have the same return and volatility characteristics and differ only in their index weighting, then both positions will have equal risk regardless of the fact that one employs short-selling and the other does not. In a long-only setting, the -3% active weight is only achievable in stock B due to the short-sale restraint. This long-only constraint acts as an artificial restriction on managers on how far they can underweight stocks and prevents them from fully implementing their target underweight positions into a portfolio. This limitation on active weights is effectively removed in an active extension portfolio. Instead of imposing a restriction that all portfolio weights are greater than zero, the constraint instead imposes that the sum of short portfolio weights is capped at a fixed level, such as 30% in a 130/30 portfolio.

Since tracking error risk depends on the size of the active positions and not the size of portfolio weights, portfolio risk does not depend on the level of short selling employed. This can be shown by using the example of two portfolios created using a portfolio optimisation algorithm on the same information set and high tracking error target, one of which has the constraint of no short selling. Chapter six provides details on the data and method used to perform this optimisation. Figure 2.5 shows the results of the portfolio construction at a target tracking error of 6%, with the portfolio weight displayed on the y-axis against the individual stocks ranked in order of size on the x-axis. In the long-only example shown in Figure 2.5, the portfolio weights are concentrated into a small number of stocks expected to outperform to best utilise the manager's 'buy' ideas within a high risk target. This creates a skew towards the utilisation of 'buy' ideas against the 'sell' ideas, as due to the restriction on short-selling the average overweight position is much larger than the average underweight position.

The second portfolio, displayed in Figure 2.6, shows the active weights from the portfolio construction for the same set of forecasts and tracking error target with the long-only constraint removed. When short selling is introduced, the concentration seen in a small number of large long positions in the first portfolio are no longer present, as the active weights can be more evenly distributed by the portfolio optimiser over a mix of overweight and underweight positions. As a result, the transfer coefficient is higher after the long-only constraint is removed. Although the portfolios are constructed with the same level of risk, the portfolio with short positions more efficiently allocates the active positions across the manager's buy and sell ideas. This will be shown later to lead to a higher risk/reward combination.

Figure 2.5: Example long-only concentrated portfolio, TE = 6%, TC = 0.43

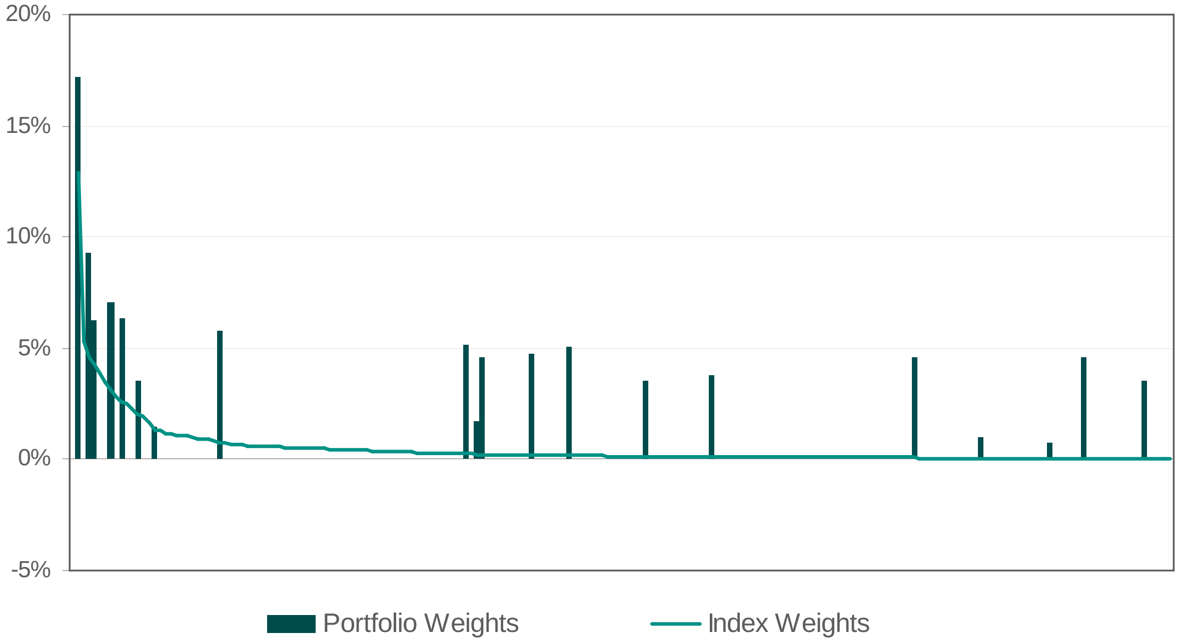
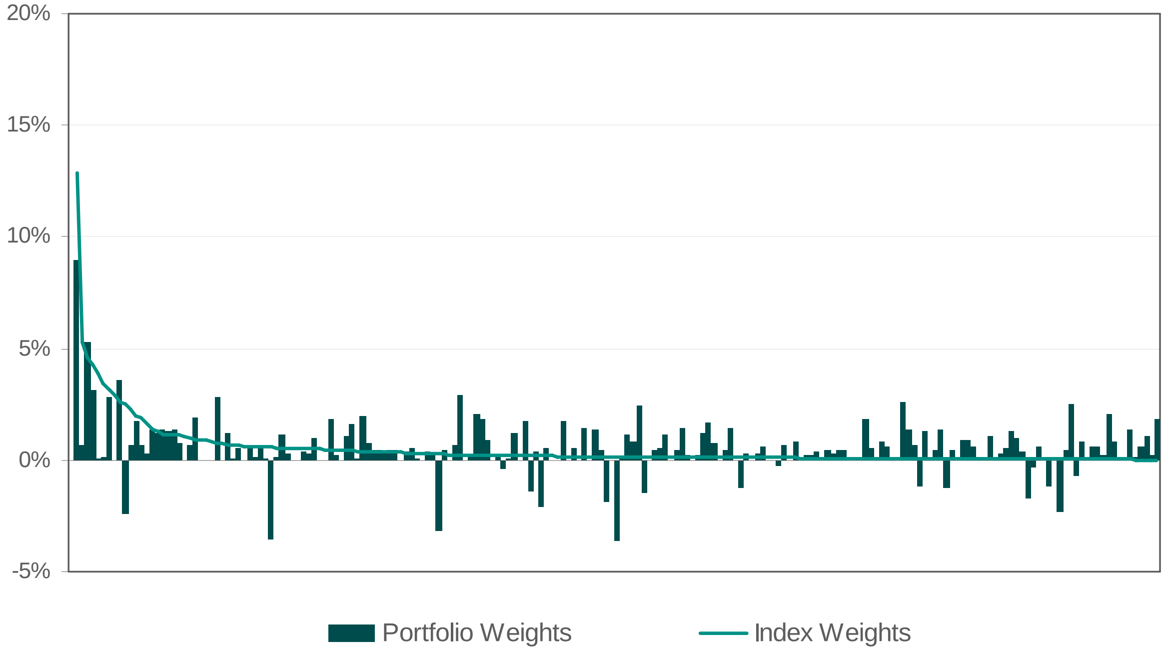


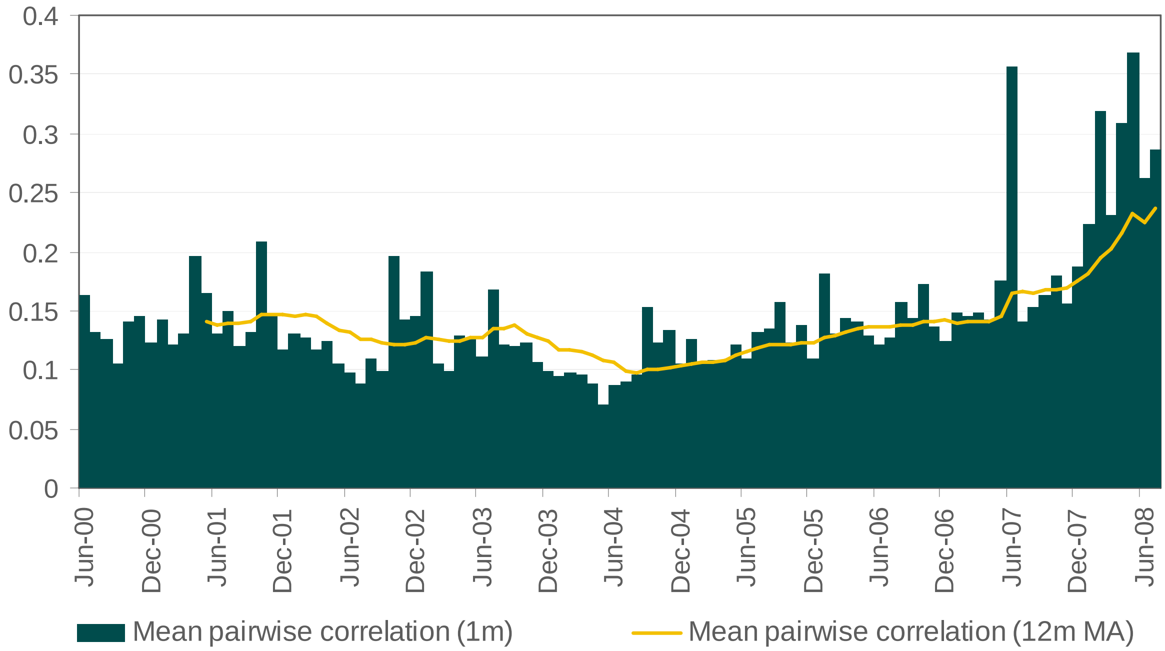
Figure 2.6: Example 130/30 portfolio, TE = 6%, TC = 0.68



An implication of the above is that the benefit of introducing short-selling is positively related to the tracking error target. While portfolios with higher target levels of tracking error will benefit the most from the introduction of short-selling, this effect is lower for stocks with lower risk targets. Generally speaking, funds with lower risk targets will take smaller active positions against the index to lower the volatility of their active component of returns. If active positions are on average lower, they are less likely to be constrained by the requirement to only take long positions. In the case of funds with low tracking error limits such as enhanced index funds, which aim to outperform the index by a small margin with a low level of volatility relative to the index return, there may be little benefit in relaxing the long-only constraint as the active positions taken will likely not be meaningful enough to benefit from short-selling.

An additional motivation for the introduction of active extension strategies identified by Montagu (2007) is the decrease in dispersion across individual stock returns over the past decade. An argument put forward by Clarke, de Silva and Sapra (2008) is that in environments of higher correlation between security returns, larger active positions are needed to achieve the same level of active performance. In terms of the Grinold and Kahn (1989) model, there is less breadth available as the active positions taken will be highly correlated with one another. In order to achieve the same target level of outperformance, larger active positions need to be taken in periods of high correlation between individual security returns. Figure 2.7 shows the average pairwise correlation of securities in the S&P/ASX 200, calculated using rolling 12-month periods. Using the 12-month moving average as a smoothed measure of pairwise correlation, it can be seen that the correlation between stocks in the S&P/ASX 200 index has increased over the past eight years.

Figure 2.7: Average pairwise correlation, S&P/ASX 200 constituents



With less correlation in individual stock returns, an active manager can take smaller active positions for the same level of tracking error. Due to the smaller active positions, they are less likely to be inhibited by the long-only constraint resulting in the benefit of an active extension strategy being lower. Conversely, the effect of an increase in pairwise correlation on active managers is a lower level of outperformance from their stock selection, as the ability to pick outperformers or underperformers is decreased by a higher correlation between individual returns and the broader market. Consequently, to increase their returns managers need to increase the absolute size of their active positions to gain more performance out of their best ideas. As the underweight positions are increased, they are more likely to run up against the constraint of no short selling, leading to the formation of concentrated long-only portfolios and the under-utilisation of short-side ideas. In an environment of low dispersion across individual stock returns, active extension portfolios should negate the need for highly concentrated portfolios by allowing diversification into a larger number of active positions while more efficiently utilising the manager's information set.

Additionally, an increase in overall market volatility has been shown by Clarke, de Silva and Sapra (2008) to decrease the benefit from introducing short positions into a long-only portfolio. Holding all other factors equal, in periods of higher market volatility active weights need to be smaller in order to achieve the same desired level of tracking error. Using the Grinold and Kahn (2000a) framework, higher stock volatilities will lead to higher expected alphas, which in turn reduce the weightings in the portfolio through the optimisation process. If active weightings are lower, the long-only constraint becomes less of a restriction and the resulting performance increase in relaxing the short-selling constraint is lower.

In short, active extension strategies essentially allow managers to optimise their portfolios and equally take advantage of all information available to them. Although gross exposure of the fund increases due to extra positions on the long and short side, this does not necessarily lead to a higher level of risk. Allowing short-selling permits managers to increase the potential size of active underweight positions they can take. When looking at performance on a risk-adjusted basis, this allows managers to construct more efficient portfolios.

2.3 Costs of active extension strategies

Although the introduction of short-selling can allow a manager to increase returns, it also generates a higher level of costs. The first explicit cost comes from the increased level of trading within the portfolio. Due to the higher number of positions in the portfolio relative to a long-only portfolio of the same size, more trading is required to enter and exit these positions. For example, a typical 130/30 portfolio with a 30% shorting level has a gross number of positions to 160% of the value of the fund due to the extra 30% of positions on both the long and short side. Assuming the same proportion of positions are traded in the 130/30 fund as in a long-only fund, turnover will increase by 60%. Considering that many investors use trading stops as a risk control to prevent short positions from growing too large if loses are encountered, this may further increase the level of turnover. This increased trading volume translates to an additional cost through the payment of brokerage commissions and any implicit spread or market impact costs incurred. Higher trading costs act as a drag on portfolio performance, reducing the net benefit of an increase in short-selling.

The natural drift of portfolio weights away from their target weights, known as passive portfolio drift, also incurs a cost as rebalancing back to target weights requires additional trading. If the securities held in the long component of the portfolio underperform (outperform) the securities held in the short component, the size of the short positions relative to the size of the long positions will decrease (increase). For example, if the long assets of a 130/30 fund decrease from \$130 to \$120, while simultaneously the short positions decrease in value from -\$30 to -\$40, the fund has passively drifted to a 150/50 allocation. Rebalancing back to a 130/30 allocation requires realising these losses by closing out some of the long and short positions. This characteristic is, by definition, not shared with long-only portfolios, resulting in a hidden cost of rebalancing to maintain target levels of shorting.

An additional cost in the practical implementation of an active extension model is the cost of funding for the additional long positions. Although standard financial theory invokes the concept of a self-financing portfolio that incurs no cost to obtaining leverage, this idea is argued by Qian, Hua and Sorensen (2007a) to be unattainable in practice. When implementing an active extension portfolio, the short positions cannot be fully used to fund the additional long positions due to margin constraints. Proceeds from short sales are kept with the prime broker as cash or in cash-like securities, with interest paid to the investor less a spread kept by the broker. The incremental amount invested in the long side of the portfolio is borrowed from the prime broker, typically at a margin above the cash rate. The resulting funding spread between the funds borrowed and the cash held as collateral on short sales represents an extra cost to the active extension strategy.

In order to short-sell, the stock must first be borrowed. The cost of stock borrow varies depending on the availability of stock lent by institutions and the demand from other short-sellers. Stocks with a larger capitalisation will typically have a higher availability and lower cost of stock borrow. The cost of stock borrow may also vary depending on whether there are any corporate actions related to the stock. Stocks involved in takeover activity will typically have an increase in stock borrow costs as merger arbitrageurs will look to borrow stock to undertake pair trading on the target and the acquirer. In a capital raising such as a rights issue, institutions may call back their stock so as to be eligible to receive rights, decreasing supply in the market for stock borrow and increasing the costs for short-sellers. Although these represent some of the factors that influence the cost and availability of stock borrow, this is not an exhaustive list and there are myriad factors that may influence borrowing costs. In short, the requirement to borrow stock in order to short-sell introduces an extra cost and complexity that does not exist in long-only portfolios.

In addition to the explicit costs of this type of strategy, there are a number of practical issues that need to be considered when implementing an active extension strategy. The most apparent issue is in the added complexities of taking a short position in a stock relative to taking a long position. In order to take short positions, it is necessary for the manager to have a relationship with a prime broker who is able to lend shares to the fund. This requires paying a fee to the prime broker and introduces the possibility of counterparty risk on collateral held with the prime broker if the contract with the prime broker is not correctly structured. As outlined above, the availability of stock borrow depends on a number of characteristics of the stock. The short seller also has an obligation to pay any dividends on the stock and mirror the effect of any corporate action such as stock splits or rights issues.

The right of stock-lending institutions to call back their stock at any time creates an added risk and potential cost. If lenders start to call their stock back, a resulting decrease in the availability of stock to borrow will result in an increased borrow cost. If a manager has already shorted the stock at this point, the original owner of the stock may exercise their right to call back the lent stock at any time. Anecdotal evidence suggests recalls are low for highly liquid stocks, as when an institution wishes to recall stock that is on loan prime brokers are able to cover the borrower's position by simply borrowing from another institution. If this is not possible, there may be a 'short squeeze', where the shorter may be forced to close out their short position by buying in a short period of time, possibly incurring market impact costs if it requires a large volume in an illiquid security. If other short-sellers are forced to buy on-market at the same time, the resulting trade imbalance may result in higher buying prices.

The addition of short positions also requires a higher attention to risk management. Theoretically the potential loss on a short position is infinite as the capacity for share price increases is unlimited, whereas for long positions the maximum loss per position is capped at 100%. In a well diversified active extension portfolio it is unlikely that a single short position could present a significant risk to a large decline in the overall portfolio. Like long positions, the size of a short position will increase as the underlying stock increases in value, resulting in the size of the position increasing when there is a loss. The possibility of stock being recalled at any time and the higher potential for loss tends to give short positions a shorter duration than long positions, resulting in higher trading costs from the increased turnover required to enter and exit positions (D'Avolio, 2002). Short sales are also subject to higher regulatory requirements, and in the Australian market currently there is uncertainty as to how these regulations may change following a temporary ban on short-selling ASX-listed securities.

It is important also to note that the increased performance of active extension portfolios over long-only portfolios is contingent on the manager having some skill in identifying outperforming and underperforming stocks. As with any active strategy, if the underlying stock selection process is not able to select potential outperformers or underperformers, it will perform in-line with the broader market on average and will possibly underperform after fees and transaction costs. Although active extension strategies allow managers to leverage their active returns to the performance of their stock selection model, the opposite is also true. If the stock selection model has negative alpha over a period of time, the active extension structure may increase underperformance relative to a long-only portfolio. Therefore it is important to realise that active extension strategies are not in themselves a source of high performance, and only provide the means for a skilled manager to increase their exposure to their stock selection process. In the absence of a skilled manager or a high-performance stock selection model, there is no reason to believe that an active extension strategy will outperform an equivalent long-only portfolio or its benchmark, and after the increased costs necessary to implement short selling the active extension portfolio may underperform.

2.4 Quantitative and fundamental processes

There is also an additional human element in whether managers have equal skill in picking potential short positions as they do for long positions. Managers who have experience in traditional long-only management using a fundamental stock selection process will have developed skills in identifying stocks that are fundamentally undervalued; however these skills may not necessarily transfer into selecting stocks that are overvalued. Managers who discard from their stock selection process stocks they consider unattractive and concentrate their research on a subset of attractive stocks will have to expand their research to encompass both attractive and unattractive stocks to identify potential candidates for short positions. In addition to difficulties in stock selection, managers who are not familiar with the operational issues associated with short selling may not be suited to implementing an active extension strategy.

These problems are less likely to apply to managers using a quantitative stock selection process, where the returns for all securities in the investment universe are explicitly forecasted. Quantitative managers typically use factor models to rank all stocks in their investment universe in order of attractiveness based on past correlation between factors and subsequent returns. In contrast, a fundamental manager may only have the resources to analyse a smaller set of stocks. In the case of quantitative management there is no disparity between identifying potential short and long positions, as a typical quantitative model is able to forecast with a similar degree of accuracy stocks that can underperform or outperform.

Quantitative strategies are also highly scalable, in that an existing model can be applied to an enlarged investable universe with relative ease. Middleton (2007) identifies that there may be a marketing advantage for quantitative managers as they can take existing models and back-test their performance in an active extension portfolio to demonstrate past performance. Quantitative stock-selection models are often paired with portfolio optimisation methods to determine portfolio weights as quantitative stock selection models are able to generate forecasts for returns and dispersion for all stocks in the investment universe. Quantitative strategies also often take a detailed approach to managing risk, which is an important requirement of active extension strategies given that they introduce a number of additional market and operational risks relative to long-only portfolios.

The advantages of active extension strategies to quantitative managers are reflected in the rapid growth of active extension strategies over the past decade with an estimated 60-80% of funds based on a quantitative process (Johnson et al., 2007). Quantitative managers such as State Street and Barclays Global Investors were responsible for most of the early implementations of active extension strategies; however the number of active extension strategies offered by fundamental managers is increasing (Middleton, 2007). Despite the dominance of quantitative funds, the benefits of active extension strategies apply to both fundamental and quantitative processes. This study takes an approach to stock selection and portfolio construction that mimics a quantitative strategy to reflect the dominance of quantitative management of active extension portfolios. However, the implications drawn from the conclusions of this study should apply to both quantitative and fundamental-based active extension strategies.

3. INSTITUTIONAL BACKGROUND

This section provides some background into the regulation of active extension funds and gives an overview of the major fund providers and investors. An important determinant of the growth in active extension strategies has been the regulatory environment. Most developed markets have a greater degree of restrictive regulation on short selling and the operation of active extension funds relative to long-only portfolios. Restrictions are also often placed on the nature of funds that can be marketed to retail investors. Other regulation restricts the allocation to alternative or hedge fund strategies by pension funds and other institutional investors. Recently, relaxing of existing regulation on the use of short selling within funds has provided a catalyst for the growth of active extension funds. Regulation on short selling also affects the operation of active extension funds and provides an additional complexity relative to long-only portfolios. Although there is growing acceptance that it is not appropriate to group active extension strategies with alternative strategies such as hedge funds, there are still greater regulatory obstacles with marketing and operating active extension funds than with long-only funds.

3.1 Australian regulation

An important catalyst for growth in active extension funds in Europe and the US has been the easing of regulation restricting the amount of exposure and use of short selling in funds marketed to retail investors. In these jurisdictions, different rules apply to how long-only funds and hedge funds operate and how they can market funds to investors. Due to the short selling and leverage employed in active extension funds, regulation such as UCITS III in Europe and Regulation T in the US provides more onerous obligations than apply to long-only funds. In Australia, long-only funds, active extension funds and hedge funds can be set up as Managed Investment Schemes (MIS), and thus are subject to the same level of regulation. As a consequence, active extension funds can be marketed to retail investors with the same set of organisational and disclosure requirements as traditional long-only funds. By regulating active extension funds and long-only funds under the same system, this provides a less onerous regulatory structure for active extension funds than the current system in Europe or the US.

Short sales in the Australian equities market are regulated by the Australian Securities Exchange (ASX) and by the government regulator, the Australian Securities and Investments Commission (ASIC). Short sales on the ASX can broadly be defined as being 'naked' or 'covered'. Naked short sales are regulated by the Corporations Act and disclosed to the ASX, which sets strict limits on which securities are allowed to be sold short and the maximum allowable level of short sales. In addition, the total number of outstanding short sales is disclosed to market participants by the ASX. 'Covered' short sales, which anecdotally are the predominant method of shorting for institutional investors, are executed by borrowing stock through a prime broker or custodian to meet settlement obligations. The common interpretation by market participants is that covered short sales do not constitute short sales as defined in the Corporations Act, as stock lending arrangements transfer legal ownership of the underlying security to the short seller.[11] Covered short sales, until recently, have been relatively unregulated and were not disclosed to other market participants.[12]

[11] King (2005)
[12] ASX consultation paper (2008)

3.2 International regulation

Regulation in the US and Europe provides a more restrictive set of rules for active extension funds than for traditional long-only funds. In the US, retail mutual funds must comply with 'Regulation T' which restricts the amount of leverage that can be employed within a fund. Effectively, it limits gross exposure to no more than twice the net assets of the fund, resulting in a maximum 150/50 short-selling level on mutual funds marketed to retail investors. Running a 150/50 fund within these limits is difficult in practice, as passive portfolio drift can cause the relative size of short positions to increase beyond the 50% level. Mutual funds and other investment companies regulated under the Investment Company Act of 1940 are prevented from relinquishing custody of their long positions to a broker, meaning that they are unable to pledge shares as collateral and are subsequently subject to higher financing costs and lower potential levels of leverage. Hedge funds have lower regulatory constraints and are not subject to the same restrictions as mutual funds, however there are restrictions in place on offering hedge funds to retail investors.

A similar regulatory structure applied to European funds is UCITS III, instituted in 2001 as a set of less restrictive regulations on the structure of funds that can be marketed to retail investors. Under these regulations the total long position in physical securities may not exceed 100%, however the gross position may be increased up to 200% through the use of derivatives. Pledging securities in respect of margin requirements for derivative positions is allowed, providing the security meets certain liquidity requirements (Donohoe, 2006). UCITS III also prevents physical short-selling, requiring short derivative positions to underweight securities. Given the gross position limit of 200%, in an active extension strategy the maximum active extension strategy allowed is 150/50. Although this analysis does not consider the use of derivatives, the results should also apply to funds that use derivatives to gain exposure given that derivative exposure can essentially be replicated in the underlying cash equities market.

3.3 Key institutions and investors

Active extension strategies are predominantly provided by institutions that have backgrounds in quantitative strategies and have experience providing other long-short products to investors. Table 3.1 gives a summary of the largest active extension providers by funds under management. Most of the largest providers use a quantitative approach, mirroring the findings by Johnson et. al (2007) that 60-80% of active extension strategies are driven by quantitative processes. Most of the larger funds also have experience providing existing strategies that use short selling.

Table 3.1: Largest active extension managers, globally

	Total active extension (US$m)(1)	Quantitative or fundamental process	Offers other long-short strategies
State Street	11,726	Quantitative	Yes
Barclays Global Investors	5,000	Quantitative	Yes
Jacobs Levy	4,891	Quantitative	Yes
Goldman Sachs AM	4,000	Quantitative	Yes
Analytic Investors	3,487	Quantitative	Yes
Aronson Partners	3,311	Quantitative	Yes
JPMorgan AM	3,291	Fundamental	Yes
Acadian AM	2,509	Quantitative	Yes

(1) Source (FUM): Pensions and Investments, as of 30 September 2007

The largest uptake in active extension strategies globally has been from pension funds. As of August 2007, pension funds owned 35% of global equities (Watson Wyatt, 2007) and were responsible for most of the $50bn invested in active extension strategies (Middleton, 2007). In effect, the aim of pension funds is to meet pension liabilities with the lowest level of contributions necessary, which is achieved by maximising returns in the intervening years. Active extension strategies offer pension funds the same exposure to market returns as long-only funds, but with added scope for outperformance over market returns. In the notation of Jensen (1968), they combine the beta exposure of long-only funds with the ability of a hedge fund to generate additional alpha, assuming the manager has the ability to outperform. This represents an appealing combination to pension funds that rely on market returns to meet their long-term liabilities but also seek a 'kicker' in the form of outperformance against the market to enhance returns. It is for this reason that pension funds have been utilising active extension strategies as a replacement for 'core' long-only equity strategies in their portfolios, with 58% of US defined benefit plans as of April 2007 either using or seriously considering active extension strategies (Pyramis, 2007). The high take-up of active extension plans by pension funds in the US and Europe has been mirrored by some of the larger superannuation funds in Australia, with HESTA, Hostplus, Care Super, JUST Super and SPEC Super allocating some of their portfolios to active extension strategies.

An alternative active strategy to pension funds other than active extension strategies are market-neutral hedge funds. Currently, hedge funds comprise at most only 5-10% of asset allocation for pension funds (Stewart, 2007). Although market-neutral hedge funds can provide a source of returns with low correlation to the broader market, their lack of exposure to market returns makes them unsuitable for meeting long-term pension liabilities. To provide long-term returns, market exposure provides the means by which pension funds can achieve long-term growth. One of the reasons active extension funds are being adopted by the pension fund industry is that they provide an effective crossover between long-only funds and market-neutral hedge funds, by providing beta exposure while lifting restrictions on the managers' ability to pursue outperformance. This exposure to market returns allows pension funds to invest a larger proportion in an active extension fund or fund of funds than they currently assign to hedge funds in order to maximise exposure to both market returns and outperformance.

The take-up of active extension funds has so far been predominantly led by institutional investors such as pension funds, with few retail active extension funds on offer. One possible explanation may be the dominance of quantitative active extension strategies, with 60-80% of active extension portfolios estimated to be run using a quantitative approach (Johnson et al., 2007). An argument put forward by Iyer (2006) is that retail investors may not be attracted to quantitative strategies as the process of selecting investments by a statistical model may seem counterintuitive, or inferior to a fundamental process that involves detailed research and company visits. An additional consideration may be that regulation in the US and Europe has previously been highly restrictive on the use of shorting in retail funds, resulting in the offerings of active extension funds to retail investors lagging that of institutional investors. It is also possible that some retail investors may also view the use of short selling as being highly speculative or detrimental to the market.

4. LITERATURE REVIEW

4.1 Early portfolio construction literature

The origins of modern portfolio theory lie with the seminal work by Markowitz (1959) who formulates a clear mathematical approach to creating portfolios that optimise risk-adjusted returns to investors. Markowitz's work divides the process of portfolio construction into two distinct steps of forming a set of beliefs about future security performance and implementing these beliefs through the construction of an efficient portfolio. An additional proposition was that diversification was crucial to minimising variance for utility-maximising investors. Sharpe (1963) expanded on this work by postulating that assets are priced based on their beta, a measure of sensitivity to movements in the overall market. These seminal works showed that portfolio construction is in effect an optimisation problem and highlighted the importance of diversification in achieving an optimal risk-return tradeoff. The insights of Markowitz and Sharpe, among many others, provide the groundwork for modern portfolio theory.

4.2 Active management literature

In the past two decades, a subset of portfolio theory has been created based on active management of portfolios. The main concept behind active management literature is that active managers have the goal of outperforming market returns with the lowest amount of deviation relative to the benchmark, rather than aiming to form a portfolio that overall has a high reward/risk tradeoff. Much of the work in the area of modern active management theory can be traced back to Grinold (1989), who introduces the 'fundamental law of active management' equation as:

$$IR = IC.\sqrt{N} \tag{4.1}$$

where IR is the observed information ratio, a measure of risk-adjusted outperformance, IC is the information coefficient given by the correlation of forecast security returns with realised security returns, and N is the number of securities in the investment universe. Although Grinold acknowledges that the fundamental law is approximate in nature, the important intuition is that returns are a function of information level, breadth of investment universe and portfolio risk.

Clarke, de Silva and Thorley (2002) extend the seminal ideas of Grinold (1989) by introducing the idea of a transfer coefficient to measure the efficiency of portfolio implementation. The transfer coefficient measures how efficiently forecast returns are implemented into portfolio construction. A simplifying assumption of the Grinold (1989) framework is that managers have no restrictions in how they can construct a portfolio from the information set they possess. Grinold himself states that the fundamental law "gives us only an upper bound on the value we can add" because of the assumption we can "pursue our information without any limitations". Clarke, de Silva and Thorley (2002) modify the fundamental law to incorporate a 'transfer coefficient' which measures the efficiency of portfolio implementation. In terms of the Grinold (1989) framework, portfolio performance as measured by the information ratio is roughly equal to the information coefficient times the transfer coefficient:

$$IR = TC.IC.\sqrt{N} \tag{4.2}$$

In effect, the transfer coefficient acts as a scaling factor on the level of information. This is an important result, as it infers that portfolio outperformance is driven not only by the ability to forecast security returns but also by the ability to frame those security returns in the form of an efficient portfolio. The implication is that managers who are skilled at forecasting security returns need to be able to construct an efficient portfolio to maximise the benefit from their information. Assuming the construction of an efficient portfolio in the absence of any constraints, the transfer coefficient will be equal to one. Constraints on portfolios lower the transfer coefficient as they place limits on how efficiently managers can construct portfolios that reflect their forecasts.

4.3 Empirical analysis of active extension strategies

Clarke, de Silva and Thorley (2002) also extend their analysis with a Monte Carlo simulation of example portfolios constructed from the constituents of the S&P 500, subject to a set of constraints. The effect of size-neutrality, sector neutrality, value-growth neutrality, maximum total number of positions and long-only constraints are analysed by the authors. They find that the long-only constraint is the most significant restriction placed on portfolio managers, but point out that by nature of its ubiquity is often ignored as a constant that affects portfolio construction. Subsequent literature uses the framework developed by Clarke, de Silva and Thorley (2002) to examine the effects of the long-only constraint on the transfer coefficient.

The effect of constraints on portfolio efficiency, measured by the transfer coefficient, is further studied in a later paper by Clarke, de Silva and Sapra (2004). The authors look at a broad range of constraints, including market capitalisation, industry, sector, active weight and short sale restrictions. Two series of optimisations are run to show the impact of the long-only constraint on portfolio efficiency, with optimisation constraints of a beta-one portfolio subject to a tracking error limit. The marginal performance increase of increasing short-sales is found to be diminishing, with the performance increase from moving from long-only to 110/10 greater than that from moving from 110/10 to 120/20. The authors find that as tracking error increases the effect of the long-only constraint is intensified, resulting in a lower transfer coefficient as tracking error is increased. A trade-off exists between the maximum possible transfer coefficient, the level desired level of tracking error and level of shorting. As tracking error increases, the transfer coefficient will decrease unless the level of shorting is also increased. The inference from this is that the optimal level of shorting is positively related to the targeted level of tracking error. The authors conclude that the short sale constraints in a long-only portfolio cause the most significant reduction in portfolio efficiency.

An analysis by Foley (2006) shows the differences in implementation of active extension strategies over various US equity indexes. The common factors put forward by Foley as affecting the attractiveness of active extension strategies are the impact of benchmark weight distribution, level of manager skill and tracking error target. Similar to the analysis by Clarke et al. (2002, 2004), Foley's analysis uses a simulation approach, with measures in the changes of the transfer coefficient as a means of analysing the benefits of active extension strategies at different levels of shorting. The simulated portfolios are constructed using a mean-variance framework with the desired level of tracking error found as a function of the level of investor risk aversion. Foley finds that portfolios benchmarked to small and mid-cap indexes exhibit the greatest benefit from introducing active extension strategies, even after adjusting for the higher cost and difficulty in shorting these stocks.

Sorensen, Hua and Qian (2007) examine the added costs and benefits associated with an active extension structure relative to a long-only structure. The authors view the long-only constraint as being highly restrictive on the ability of managers to outperform their benchmarks. Similar to Clarke, de Silva and Sapra (2004), they analyse the effects of tracking error constraints through a series of simulations. Simulated manager forecasts are backed out of realised returns, assuming a level of skill given by the information coefficient. Portfolios are then constructed using an optimisation method subject to a constraint on the total level of short selling and tracking error target. The authors also incorporate the effect of higher transactions costs, finding after costs that the benefits from active extension portfolios are still positive. The optimal degree of shorting was shown empirically to be a function of manager skill, desired risk target, turnover, leverage and trading costs. The important implication of this analysis is that there is no universal optimal level of short selling in an active extension portfolio. Instead, an appropriate level of short selling will depend on a combination of factors endogenous to each fund, such as manager skill and tracking error targets, and factors common to the market such as trading costs, stock borrow costs, volatility, benchmark concentration and market breadth.

Johnson, Kahn and Petrich (2007) construct a similar model for historical back-testing of 130/30 portfolios, using stock returns over the period from 1994-2006 for their model. The stock selection model chosen mimics those used by quantitative investors, using a factor ranking methodology based on factors of analyst estimate revisions, long-term price momentum and common valuation multiples. The portfolio is rebalanced monthly based on changes in rankings. The authors find that the simulated 130/30 portfolio returns an average annual Cumulative Average Gross Return (CAGR) of 11.0% compared to the long-only portfolio, which returns 7.6%. On a risk-adjusted basis, the returns as measured by the information ratio were higher for the 130/30 portfolio than the long-only portfolio.

Armfelt and Somos (2008) conduct a similar study using historical equity returns to analyse the hypothetical performance of active extension portfolios at various levels of leverage relative to a long-only portfolio. Twenty-five Fama-French portfolios formed on size and book-to-market ratios are used in the analysis over a long historical period of 1927-2007. The authors find that in the range from 100/0 to 150/50, the 150/50 portfolio with the highest gross exposure had the highest performance over the 80-year period after adjusting for transaction costs. The average CAGR of 130/30 strategies for the 80-year period is 16.4%, outperforming the long-only average CAGR of 14.6% and benchmark index CAGR of 10.2% by a statistically significant amount.

4.4 Theoretical models of active extension strategies

Johnson, Kahn and Petrich (2007) construct a theoretical framework for determining the optimal level of short selling within an active extension portfolio. Their analysis shows that using a short selling level that is too excessive or too conservative can have a major effect on the efficiency of a portfolio. Furthermore, the authors find that exceeding the optimal level of short selling causes a sharp drop off in risk-adjusted returns, implying that the costs of excessive shorting are greater than shorting levels that are too conservative. The framework is reinforced by an empirical analysis using a simulation approach by generating optimal active extension portfolios at variable levels of gearing. Although the authors attempt to quantify the optimal level of shorting, they acknowledge that finding optimality ex-ante in a real world context is a difficult exercise due to the many factors that can change over time.

In a 2008 paper, Clarke, de Silva and Sapra extend on their previous simulation-based analysis by providing a mathematical model of active extension portfolios. The model developed by the authors shows that the expected short weight for a security depends on the size of the security's benchmark weight and its expected active return. An expression for the expected benchmark weight for each security is derived based on a set level of benchmark concentration. Given the expected benchmark weight and expected active weight, an expression is derived for the expected short position per security. The sum of the expected short weights gives the expected level of short positions for the portfolio. By introducing costs, an optimal level of portfolio shorting is determined by using an approach where the marginal benefits of shorting equal the marginal costs. Using historical data, the authors apply the analytical model and find that, similar to previous empirical studies, the effective level of shorting is highly related to the accuracy of the return forecasting, target risk level, benchmark concentration and marginal costs of shorting. The authors also show that an increase in benchmark concentration and pairwise correlation between stocks increases the expected level of short selling, while an increase in market volatility decreases the desirable level of shorting.

4.5 Other active extension literature

Jacobs, Levy and Starer (1998) explore commonly held myths surrounding long-short portfolios and analyse whether long-short portfolios, both market neutral and with net market exposure, are optimal allocation choices for investors. They find that long-short portfolios which have no net market exposure are generally suboptimal choices for utility maximising investors. On the other hand, they argue that there is merit in long-short portfolios with some exposure to market returns (referred to as 'equitised long-short portfolios), given the individual has a high enough risk tolerance and the manager has some form of skill in their stock selection. Although this research predates popular introduction of active extension strategies, which are in effect equitised long-short portfolios with a constraint on having close to 100% net exposure at all times, the authors findings are generally in line with that of later analysis on active extension strategies. Jacobs, Levy and Starer (1999) extend on these findings in a later paper which examines the characterisation of long short portfolios. The authors propose that constructing long-short portfolios that have no exposure to systematic risk is not necessarily optimal. Long-short portfolios with market exposure are also argued to be more similar to traditional long-only portfolios than market-neutral long-short funds.

Following Jacobs, Levy and Starer (1998, 1999) who analyse long-short portfolios with market exposure in comparison to market neutral long-short portfolios, Jacobs and Levy (2006) analyse their efficiency in relation to long-only portfolios. The authors show that, assuming long positions can be used as collateral on short positions, proceeds from short positions can be used to fund additional long positions, thus negating the issue of funding costs. Anecdotal evidence suggests this is common practice by prime brokers in the Australian market. The level of performance increase from active extension strategies is shown to be a function of what the limits on risk are, as measured by tracking error. The authors also argue, as in Jacobs and Levy (1996) that artificial constraints on tracking error lead to suboptimal results for investors. However in practice constraints on tracking error are commonly used as a means of risk control.

Jacobs and Levy (2007a) extend their previous analysis to a comparison of active extension portfolios to equitised long-short portfolios, which are a combination of market-neutral long-short portfolios with market exposure through an index Exchange Traded Fund (ETF), index swaps or futures contracts. The popularity of this investment style comes from a recent industry trend towards 'portable alpha', where a portfolio is divided into a low-cost source of index exposure such as an ETF to provide 'beta' and a market-neutral active strategy to provide the 'alpha' component. Notionally, an equitised long-short portfolio shares many characteristics with active extension portfolios, having a similar degree of market exposure while retaining the ability for managers to take long and short active positions in stocks. The authors argue that an active extension fund provides a superior alternative to the combination of market neutral funds with added index exposure due to lower costs of implementation, as a combination portfolio would lead to added costs from some stocks being simultaneously held long and short. Given this advantage of active extension portfolios and the interchangeable nature of the two strategies, Jacobs and Levy (2007a) propose that active extension strategies are the optimal alternative of the two.

Gastineau (2008) provides an alternate method of portfolio construction suitable for fundamental managers who do not have skill in identifying candidates for short positions. Gastineau proposes that managers can short-sell sector ETFs or buy special 'short ETFs' as a method of taking a short position while minimising exposure to idiosyncratic risk. ETFs are also advantageous in that they are easy to borrow with no material risk of a short squeeze as market makers are usually able to easily create new units in an ETF for lending at a low cost. If an institutional investor does not have the analytical ability to identify individual short positions, the ability to handle risk management or strong enough relationships with prime brokers to implement short positions, Gastineau suggests the use of ETFs as an intermediate step towards a full active extension implementation. In this way a manager who is lacking in the skills or the operational processes to move from a long-only to an active extension strategy can still capture some of its benefits.

4.6 Active extension indexes

Lo and Patel (2008) propose the use of an index specially designed for active extension portfolios. The composition of the index mimics the approach taken by institutional quantitative investors by constructing portfolios based on ten commonly used quantitative factors combined with a portfolio optimisation method. The authors argue that a passive benchmark need not be necessarily weighted by size, and draw upon recent work by Arnott, Hsu and Moore (2005) in formulating a 'fundamental index' where weights are determined by historical fundamental factors. Similarly, the 130/30 index proposed by Lo and Patel uses a predetermined set of rules on forecasting individual stock returns based on quantitative factors, with the exact weights determined by a portfolio construction using the proprietary BARRA system. The idea of a special 130/30 index has been adopted by both S&P and Credit Suisse. S&P has created an index called 'S&P 500 130/30 Strategy Index', composed of weightings equal to the S&P 500 index weightings, plus an extra 1% for attractive stocks or less 1% for unattractive stocks as chosen by a proprietary quantitative model named STARS.[13]

[13] S&P 500 130/30 Strategy Index Methodology. Retrieved 10 July 2008, from http://www2.standardandpoors.com/spf/pdf/index/SP_500_130-30_Strategy_Index_Methodology_Web.pdf

Credit Suisse has also announced the introduction of a 130/30 index based on the construction method outlined in the paper by Lo and Patel (2008).[14]

Despite recent innovations in creating new benchmarks for active extension portfolios, traditional market capitalisation weighted indexes will be used for the purposes of benchmarking in this thesis. A market capitalisation-weighted index provides an average of all equity portfolios in an investment universe weighted for portfolio size, such that the sum of all weighted portfolio outperformance and underperformance is mathematically equal to zero. It also provides a passive alternative, as the naïve alternative to an active strategy would be to buy the index. The construction techniques of these new indexes depend on an arbitrary choice of quantitative factors, and are not commonly accepted as benchmarks. In addition, it is difficult to justify how the indexes can proxy market risk better than established market capitalisation weighted indexes can.

4.7 Literature review summary

Table 4.1: Summary of previous research into active extension strategies

Grinold (1989)	Formulated the fundamental law of active management, which expresses risk-adjusted performance as a function on manager skill and size of investment universe (breadth).
Jacobs, Levy and Starer (1998)	Found market-neutral long-short portfolios to be an inferior for utility-maximising investors to equitised long-short portfolios.
Jacobs, Levy and Starer (1999)	Equitised long-short portfolios (equivalent to active extension portfolios) have a greater deal of similarity to long-only portfolios than market-neutral long-short funds.
Clarke, de Silva and Thorley (2002)	Extend the fundamental law of active management of Grinold (1989) by introducing the transfer coefficient, a measure of portfolio efficiency. Constraints are tested through a Monte Carlo simulation. The long-only constraint is found to be the most significant.

[14] Credit Suisse and AlphaSimplex launch the industry's first 130/30 index. Retrieved 10 July 2008 from http://www.credit-suisse.com/news/en/media_release.jsp?ns=40513

Clarke, de Silva and Sapra (2004)	Examines the relationship between the transfer coefficient, maximum permitted level of short selling and tracking error. The effect of the long-only constraint is intensified when tracking error limits are increased. The greatest marginal increase in efficiency comes from moving from long-only to 110/10.
Foley (2006)	Analyses the effect of benchmark concentration by comparing the performance of active extension portfolios over different US equity indexes. The greatest benefit is found to be in small- and mid-cap stocks.
Jacobs and Levy (2007a)	Active extension portfolios are notionally equivalent to equitised long-short portfolios, but are more efficient as the unnecessary cost of holding some stocks simultaneously long and short is removed.
Jacobs and Levy (2007b)	Provides a theoretical rational for active extension strategies and refutes a number of perceived myths.
Johnson, Kahn and Petrich (2007)	Backtests an active extension and a long-only portfolio based on a quantitative factor model. The 130/30 portfolio gives a CAGR of 11% relative to a 7.6% return for the long-only portfolio.
Sorensen, Hua and Qian (2007)	Uses a simulation approach to analyse the performance of active extension strategies. After transactions costs, the performance of active extension strategies is higher than that of long-only funds. The optimal level of short selling to use is a function of portfolio-specific factors and exogenous market factors.
Armfelt and Somos (2008)	Studies the historical performance of active extension strategies over the period 1926-2007 in the US market. Portfolios are constructed based on the Fama and French (1993) model. The 150/50 strategy is found to have the highest risk-adjusted performance.
Clarke, de Silva and Sapra (2008)	Derives a theoretical model of active extension portfolios. The optimal short weight of a security depends on benchmark concentration, tracking error, stock selection skills and transaction costs.
Gastineau (2008)	Proposes the use of ETFs in implementing active extension strategies for managers with little previous experience in short selling in order to gain some of the benefits of active extension strategies.
Lo and Patel (2008)	Constructs a benchmark index for active extension portfolios. The index is based on a ten factor quantitative model, with the weights determined by a portfolio optimisation process.

5. HYPOTHESIS DEVELOPMENT

Previous research has made a convincing case for the advantages of active extension portfolios. The performance of active extension strategies is determined by various factors relating to both the manager and overall market conditions. The predictive skill of a manager and their target level of tracking error affect how an active extension portfolio would perform relative to an equivalent long-only portfolio and the market index. Market characteristics, such as volatility, correlation between returns and whether market returns are positive or negative can also affect the performance of active extension strategies. Specific hypotheses as to the effects of these factors are outlined below, in relation to the effect they have on the performance of active extension strategies.

5.1 Skill levels

Theoretically, managers with higher skill levels are able to benefit more from relaxing the long-only constraint (Qian, Hua and Sorensen, 2007). Increasing the short selling level only has a net benefit if the increase in outperformance is greater than the increased cost burden; therefore for a higher skill level the manager will be able to push short selling levels to a higher level until the additional costs outweigh the marginal benefits. As Foley (2006) points out, in the case where a manager has no stock picking skill ($IC \approx 0$) the optimum level of short selling will be zero, since increasing short selling levels will only result in higher costs. In the case where a manager has some predictive skill ($IC > 0$), the manager will be able to transform larger active weights into greater outperformance, leading to a higher level of performance from active extension strategies as they utilise the manager's informational advantage.

H_1: Managers with higher skill levels have a greater increase in performance from relaxing the long-only constraint.

5.2 Skew in predictive ability

One of the barriers to successful implementation of active extension strategies identified by Gastineau (2008) is the ability of the manager to be able to pick stocks that can potentially underperform in addition to picking stocks that can outperform. Managers who have previous stock-selection experience in managing long-only portfolios are likely to have developed greater skills in identifying potential outperformers than potential underperformers. Intuitively, being able to pick potential underperformers is a key concern when managing a portfolio that involves short selling. This leads to the second hypothesis:

H_2: Managers with a higher skew towards picking underperforming stocks can construct active extension portfolios with higher levels of performance.

The benefit of introducing short selling depends on the relationship between the marginal benefit of an increase in short positions against the increased costs. If the manager has a greater skill at picking underperformers, intuitively they will have greater performance from their short positions and thus a higher optimal level of short sales. In the extreme case of a manager with skill only in identifying outperformers and no skill identifying potential underperformers, there will be limited benefit from an increase in short sales and therefore the performance increase from relaxing the short-selling constraint will be lower. There will still however be some advantage in an active extension strategy by using short positions to finance additional overweight positions. An example of this is given by Gastineau (2008), who identifies that an active extension strategy can use short positions in index-tracking sector ETFs to provide greater risk-return outcomes than long-only strategies.

The outcome of this hypothesis has implications for differences between fundamental and quantitative managers. Fundamental managers may have more skill at picking potential outperformers rather than underperformers by virtue of the fact that experience in stock selection in a long-only context would have required the selection of undervalued rather than overvalued stocks. Quantitative managers who use scalabale mathematical or statistical models to forecast future stock-level performance are usually able to generate forecasts for all securities in an investment index with an equal skew in forecasting ability towards underperformers and outperformers. If these assumptions hold true, there is likely a greater performance increase to be had from active extension strategies to quantitative managers than to fundamental managers.

5.3 Risk constraints

H_3: Portfolios with higher tracking error limits have a greater performance increase from relaxing the long-only constraint.

The size of tracking error is a function of portfolio active weights and the variance-covariance matrix. In general, the tracking error of a portfolio will be proportional to the gross size of active weights. Portfolio managers usually have some form of risk constraint placed on them by investors or fund administrators in the form of a limit to tracking error. As Jacobs and Levy (2006) identify, a portfolio with a low tracking error target such as an enhanced index fund will likely have weights close to the index and is not restricted by the long-only constraint. Funds with higher tracking error targets will have higher active weight positions as managers are able to take larger sized overweight and underweight positions within the risk target. As the active weight sizes are increased, managers are more likely to run up against the short-sale constraint when implementing their underweight positions. In a long-only portfolio, managers will tend to concentrate the portfolio by holding large positions in their favourite stocks, but they are restricted from doing the opposite and going underweight in their least favourite stocks because of the long-only constraint. Funds with higher tracking error targets are more likely to be constrained by a long-only requirement and will gain the greatest increase in transfer coefficient from relaxing the long-only constraint. As Clarke et al. (2004) points out, there is a trade-off between the maximum transfer coefficient, target tracking error and level of shorting. If the portfolio has a higher tracking error target, a higher level of shorting is needed to maximise the transfer coefficient.

5.4 Costs

Transaction, financing and stock borrow costs increase proportionally to the gross exposure of the fund, which is driven by the level of short selling in the portfolio. A higher cost base will begin to act as a drag on portfolio performance net of costs, decreasing the benefits of an active extension strategy. Higher costs should decrease the attractiveness of higher levels of gross exposure, leading to a lower optimum shorting level. Whether the decrease in optimal level of shorting is material depends on the level of costs against the skill the manager possesses.

H_4: An increase in costs will lower the performance of active extension strategies.

5.5 Volatility

One of the consequences of a high risk target in a long-only context is that managers create portfolios with weightings concentrated in their best overweight selections. An argument put forward by Montagu (2007) is that in higher volatility scenarios, higher concentration may expose a portfolio to the potential for higher risk due to their lower diversification. Alternatively, an active extension strategy gives the potential for targeting a lower level of risk for the same amount of return by utilising short-side information in a portfolio with added diversification, achieving a higher risk-return outcome. In a higher volatility environment the benefits of increased diversification should increase the net benefit of increasing short-selling, leading to higher risk-adjusted returns for active extension portfolios.

H_5: Higher market volatility will increase the performance of active extension strategies.

5.6 Cross-sectional spread of returns

An analysis of cross-sectional dispersion of returns by Montagu (2007) found a sharp increase in pairwise correlations between S&P/ASX 200 stocks in the decade to 2007, suggesting that correlation between stock returns is increasing. If a manager takes active positions against the index that are expected to outperform, a high correlation between their active positions and the overall market will reduce their outperformance of the index. The implication of this for active managers is that there are lower opportunities in the market to generate outperformance. Taking an active position in a security will lead to less excess return when correlations are higher as the excess returns from that position will be more highly correlated with the rest of the portfolio. Accordingly, to reach the same level of performance managers will have to increase their active weight sizes and in doing so are more likely to run up against the long-only constraint. This leads to the following hypothesis:

H_6: A lower cross-sectional spread of returns will increase the benefits from implementing active extension portfolios.

If managers are required to increase their active weight sizes in environments of low cross-sectional dispersion, they will be more highly constrained by the long-only requirement. Accordingly, they will benefit more from introducing short positions into their portfolios. A higher level of short selling will allow managers to more efficiently distribute their higher active weights over both long and short positions in the portfolio to target a higher excess return for the same level of risk.

5.7 Market conditions

Holding all other factors equal, there is no theoretical reason to believe that active extension portfolios will perform better or worse in rising or falling markets. By definition, active extension portfolios have a constant 100% net market exposure and will have a beta approximating one if well diversified, and thus on average will perform in line with the broader market. Bear market conditions, defined as periods where market returns are below their long-term average, may be associated with changes in related exogenous factors such as market volatility, cross-sectional spread of returns or higher transaction costs due to lower liquidity. Apart from the effects of these factors, when all other factors are held equal declines or increases in the broader market should not be expected to have an impact on the ability of active extension strategies to outperform (or underperform) the broader market. This leads to the following hypothesis:

H_7: The level of outperformance or underperformance of active extension portfolios is equivalent across periods of positive or negative market returns.

The type of stock selection model may also affect performance during different market conditions, as evidenced by the significant underperformance of quant-driven active extension strategies during the market downturn in August 2007 (Khandani and Lo, 2007). However if this underperformance was a result of the type of stock selection model used, it does not necessarily suggest that active extension portfolios are predisposed towards underperformance in difficult market conditions. In terms of the Clarke, de Silva and Thorley (2002) framework, the decline in information ratio may be caused by a lower information coefficient (stock-selection skill) even though the transfer coefficient (portfolio construction efficiency) has not declined. Evidence from Montagu (2007) supports this by suggesting that active extension portfolios would have a higher mean and lower variance of outperformance over the August 2007 period. The stock selection model used in this analysis does not make assumptions about the type of stock selection model used and thus allows for an analysis of active extension strategies in different market conditions, without being clouded by any changes in the performance of the underlying stock selection model.

6. DATA AND METHOD

To analyse the above hypotheses, hypothetical portfolios are constructed based on historical returns data from stocks listed on the Australian Securities Exchange (ASX). A Monte Carlo approach is taken in simulating multiple hypothetical portfolios with different levels of short-selling to provide a backtest of how active extension portfolios would have performed over the previous eight year period. To test these hypotheses, the effect of changes in factors such as forecasting skill, skew in predictive ability and trading costs are varied, and the subsequent changes in portfolio performance over various levels of short selling are analysed. The following sections explain the portfolio construction techniques for the Monte Carlo simulation. Portfolio construction is divided into its two components of formulating our beliefs about future returns and constructing an efficient portfolio that reflects these beliefs. The following sections detail the method used to simulate these two steps of portfolio creation: generating a vector of stock return forecasts and covariance matrix, followed by constructing efficient portfolios using a portfolio optimisation algorithm. A sample of portfolios are generated using a Monte Carlo process based on an assumed information coefficient, target level of tracking error and maximum level of shorting. The performance of active extension portfolios is then measured using statistical tests of their information ratios and alphas.

6.1 Data

Data on historical stock returns and index weightings is obtained from IRESS. The analysis encompasses all stocks in the S&P/ASX 200 index from May 2000 to July

2008, including stocks added or removed due to index rebalancing by S&P. The sample covariance matrix was constructed from five years of monthly returns prior to May 2000. Where returns were not available during this period for the calculation of covariances, such as for stocks that listed after May 2000, the variance terms were set at the mean variance with covariances calculated based on the mean pairwise correlation. The S&P/ASX 200 index is chosen due to the liquidity of its constituents and the greater availability and lower cost of borrowing stock relative to less liquid securities outside the index. Total shareholder returns are used for the analysis to include the value of dividends, and accordingly portfolio performance is benchmarked against the S&P/ASX 200 Accumulation index. Monthly returns will be used for the purposes of rebalancing portfolios and calculating tracking error. The use of monthly returns is in line with similar analysis (see Qian, Hua and Sorensen, 2007 and Montagu, 2007).

6.2 Stock selection

The stock selection method is based on a quantitative forecasting procedure proposed by Grinold and Kahn (2000a) that is related to the authors' earlier fundamental law of active management. In quantitative management, the performance of stock selection models is often gauged on the level of their information coefficient, which is the correlation of forecast returns with realised returns for all securities in the benchmark. An information coefficient of zero implies the model has no predictive ability as the forecast returns do not have any relationship with realised returns. An information coefficient above zero implies that the model has some predictive ability in forecasting future returns of securities. The relative level of the information coefficient provides a measure that can be used to judge the performance of the forecasting ability of a portfolio's stock selection model.

In this study, the stock selection model used to generate forecast returns is based on the above concept of an information coefficient measuring the forecasting ability of a manager. Grinold and Kahn (2000a) provide a method for simulating a generic stock selection model, which has been adopted in a number of later papers (see Clarke, de Silva and Thorley, 2002; Ledoit and Wolf, 2003a; Qian, Hua and Sorensen, 2007b). To create each set of forecasted returns for the top 200 stocks, returns are drawn from a normal distribution with a set correlation with realised returns for that period. The correlation of forecast returns with realised returns is equal to the information coefficient, which allows for a specific ex-ante predictive ability of the stock selection model to be set for each portfolio. In essence, this involves creating forecasts by adding noise to realised returns to mimic an active manager with some skill in forecasting returns. Using a stochastic process in this way allows the simulation to mimic a potential set of forecasts by a skilled active manager by producing forecast returns that are randomised for each portfolio, but with a level of predictive ability scaled by the level of the information coefficient. The relative sizes and cross-sectional variations of the forecasts produced by the adjustment procedure are also consistent with the cross-sectional variations in security returns. Although this method uses realised returns as a basis for generating a random sample of predictive returns, the randomisation process mimics a set of look-ahead forecasts that a manager with a predetermined level of skill could produce for the same period.

Using the method of Grinold and Kahn (2000a) of generating random forecasts with a specified information coefficient (correlation with realised performance) provides a number of benefits. Firstly, no subjective assumptions are required regarding what factors should be used in the stock selection model, providing a greater degree of generalisation to different stock-selection methods. Unlike using a quantitative factor model, using the method of Grinold and Kahn's does not require a subjective assumption of what factors should be included in the model, and so the results are more generaliseable to other stock selection methods. The realised performance of these portfolios will therefore not be influenced by exposure to any quantitative factor and less prone to data-snooping bias. With a large enough sample of simulations, this should average out the inherent randomness in the model. In addition, the degree of manager skill assumed in the simulation portfolios, as measured by the information coefficient, can be varied and the effect of this variation on the efficiency of active extension portfolios can be measured. Lastly, potentially unlimited sets of simulated forecast returns are able to be generated for analysis, whereas if a factor model is used only one set of forecast returns per period will be generated. This will enable the simulation to analyse a larger sample size of simulations to make more robust inferences about the effects of short selling levels.

The main advantage of this method of stock selection stems from the fundamental law of active management. The fundamental law of active management provides a breakdown of portfolio performance into stock selection performance, portfolio construction efficiency and size of investment universe:

$$IR = TC.IC.\sqrt{N} \tag{6.1}$$

An intuition of the above is that creating an investment portfolio can be broken down into two components of stock selection and portfolio construction. The first step, stock selection, is the process by which the forecast performance for investable stocks is assessed. In terms of the above fundamental law of active management, the information coefficient represents the stock selection skill that a manager possesses. The second step is portfolio construction, which involves identifying portfolio weights that efficiently reflect the manager's forecast risk-adjusted returns for each security. Using the fundamental law above, the transfer coefficient represents the efficiency of portfolio construction, with a TC of 1 signifying weightings exactly proportional to the forecast risk-adjusted returns. In practice, portfolio constraints such as the ubiquitous long-only constraint prevent managers from creating portfolios that exactly reflect their views, resulting in an adverse effect on the transfer coefficient and hence a downward effect on the portfolio's information ratio.

This dissertation is focused on measuring the change in transfer coefficient and subsequent change in information ratio as a result of introducing short selling into long-only portfolios. Using Grinold and Kahn's (2000) methodology allows for a specific expected information coefficient to be set for each portfolio. Accordingly, the effect of short selling levels on the transfer coefficient and information ratio levels can be measured without any variance in information coefficient affecting the results. This gives the method of Grinold and Kahn (2000a) an advantage over other methods such as Armfelt and Somos (2008) and Lo and Patel (2008), which use different factor models for their stock selection. Although usage of these stock selection methods is standard in academic literature and the quantitative investment world, their performance varies naturally over time. For example, Armfelt and Somos (2008) use a Fama-French model for stock selection, which is partially based on constructing portfolios that are long 'value' stocks and short 'growth' stocks based on price-to-book values. Although value stocks have historically outperformed growth stocks over the long term (see Fama and French, 1992), the performance of value against growth is cyclical and there may be some periods, notoriously the tech boom of the late 1990's, where growth outperforms value. The performance of active extension portfolios using these models is then highly subject to how the underlying stock selection model has performed over these periods.

For the purposes of this study, the aim is to isolate any differences in performance exclusively to the level of short selling employed without being affected by the stock selection model employed. The method proposed by Grinold and Kahn (2000a) allows us to set an expected information coefficient, with some natural variance in information coefficient over time. In any case, the effectiveness of active extension strategies is highly exposed to the performance of the underlying stock selection model, and consequently if a poor stock selection model is chosen it will affect the performance of active extension portfolios using that model. For this analysis, the model of Grinold and Kahn (2000a) makes it possible to isolate changes in performance to the level of short selling, while keeping the effects of stock selection constant.

The first step in construction of each portfolio is to simulate a set of hypothetical forecasts by a stochastic process. Grinold and Kahn (2000a) provide a method to refine raw return forecasts into forecast active returns by adjusting for different levels of volatility and the accuracy of each forecast, as measured by the information coefficient:

$$ER_i = IC.\sigma_i.Z_i \tag{6.2}$$

In equation (6.2), ER_i is the forecast level of excess returns, IC is the assumed information coefficient that represents the level of manager skill and σ_i represents the estimated residual standard deviation for stock *i*. Z_i represents the 'score' for each security, which is a function of the raw forecasted return, standardised to fit a (0,1) distribution by the following transformation:

$$Z_{i,t} = \frac{raw_{i,t} - E(raw_{i,t})}{\sigma(raw_{i,t})} \tag{6.3}$$

To transform the raw forecast return into forecast outperformance, equation (6.2) is applied to the raw scores generated from equation (6.3). Equation (6.2) transforms the raw score into an expected return by multiplying by the information coefficient and level of standard deviation. The intuition behind this is that the higher the quality of the information, the more confidence it is possible to have in our forecasted raw return. As an example, for a manager with no skill and a corresponding information coefficient of zero, raw forecasts contain no information and hence the refined forecast of active returns will always be zero. For larger information coefficients the forecast returns have a larger correlation with realised returns, and hence it is possible to have a higher confidence in each forecast. Information coefficient multiplied by score gives us a unitless measure of confidence in how much to expect a security to outperform or underperform. Multiplying by the standard deviation term converts the confidence level into a refined forecast of outperformance. In effect, the raw forecast is scaled by the volatility of the stock and the skill of the forecaster to give an adjusted score that reflects how confident we are in the accuracy of our forecasts.

An approach suggested by Qian, Hua and Sorensen (2007b) is to incorporate the effects of transaction costs into the stock selection model. Portfolio turnover comes from two sources: the need to rebalance portfolios back to target weights due to security price movements, and changes in forecasts necessitating changes in portfolio weights. To implement this, the generated forecasts have an autocorrelation of 0.25 with forecasts from the previous period as suggested by Qian, Sorensen and Hua (2007) to simulate some stability in forecasts across different time periods. This reflects the intuitive notion that a manager's positive or negative view on a stock will have some consistency over time. Turnover is therefore limited to realistic levels as using a new set of forecasts for each monthly period requires the portfolio to be completely rebalanced, incurring high trading costs.

6.3 Variance-covariance matrix estimation

The second input into the optimisation algorithm is an estimated variance-covariance matrix. While the forecast security returns provide the inputs for maximising portfolio performance, the estimate of the covariance structure of security returns provides the means for minimising risk. Estimating the covariance matrix accurately is essential to creating portfolios that achieve the highest risk-reward trade-off within the set tracking error target.

Unfortunately, the portfolio weights obtained through a mean-variance optimiser are highly sensitive to changes in covariance terms. Assets with large abnormal covariances tend to cause abnormally large weightings in the portfolio optimisation process. If these large covariance estimates are the result of errors in measurement, the estimated portfolio weights will display signs of bias. The problem of sensitivity of portfolio weights to misestimation in the covariance matrix is well documented (Jobson and Korkie, 1980; Michaud, 1989). In addition to the effects of estimation errors, Green and Hollifield (1992) show that naturally occurring large covariance terms can lead to extreme negative weights within portfolios. Jagannathan and Ma (2003) suggest that the short-sale constraint acts as a form of shrinkage that prevents extreme negative weights from occurring. If the sample covariance matrix is applied across a number of portfolios with increasing levels of short selling, this will have an implicit effect of increasing the tracking error as the level of short sales increases. A higher tracking error will result in lower information ratios for active extension strategies than for long-only portfolios, creating a downward bias in performance for active extension strategies.

To provide a more accurate estimate and avoid any bias in risk-adjusted performance towards long-only portfolios, a method proposed by Ledoit and Wolf (2003b) is used whereby the sample variance-covariance matrix is transformed through a process called 'shrinkage'. In effect, shrinkage pulls the most extreme values in the sample covariance matrix towards central values, removing the presence of outliers that could cause havoc during the portfolio optimisation problem. Ledoit and Wolf (2003b) show that, using the same portfolio optimisation process, the use of shrinkage reduces tracking error and results in higher information ratios. In active management terms, this infers that applying shrinkage to the sample covariance matrix increases the transfer coefficient.

The shrinkage process put forward by Ledoit and Wolf (2003b) uses the following form:

$$\Sigma = \delta.F + (1-\delta)S \tag{6.4}$$

As in the above notation, Σ represents the shrinkage covariance estimator used for portfolio estimation, and is created by a weighted average of the sample covariance matrix, S, and a structured estimator denoted F. The sample covariance matrix is determined by the sample covariance of five years of preceding monthly returns. The structured estimator provides a target covariance structure that the sample covariance matrix is 'pulled' towards. Ledoit and Wolf (2003a) suggest a structured estimator based on the single-factor estimator of Sharpe (1963). A later paper by Ledoit and Wolf (2003b) instead suggest a simpler structured estimator consisting of the diagonal variances from the sample covariance matrix, with all the off-diagonal covariance terms calculated from the average pairwise correlation from the sample covariance matrix. This method provides easier implementation due to its mathematical simplicity. Although a covariance matrix based on average pairwise correlations provides a naïve estimate, Ledoit and Wolf (2003b) suggest it is appropriate when looking at assets from a single asset class (equities) and empirically show that it gives similar results to the method based on Sharpe (1963).

The variable δ is known as the shrinkage constant. The shrinkage constant determines what proportion of the final covariance matrix is determined by the structured component or the sample covariance matrix. The most optimal shrinkage constant to use is the value that minimises the difference between the shrinkage covariance estimator and the true covariance matrix. Fortunately, Ledoit and Wolf (2003b) provide a method by which it is possible to estimate the shrinkage constant based on an optimisation that minimises the squared difference between the shrinkage covariance estimator and true covariance estimator.

Another possible method of correlation matrix estimation that is used by institutions is that provided by the Barra portfolio analysis system. Although the estimates provided by Barra are widely used and highly regarded, the proprietary methodology used for estimating covariances is not disclosed. The model of Ledoit and Wolf (2003a, 2003b) is chosen for this dissertation as it provides a more transparent model that is intuitive and easily computed.

6.4 Portfolio construction

Portfolios are constructed from each vector of forecast active returns and a variance-covariance matrix from five years of historical returns that uses a shrinkage adjustment to reduce measurement error. Given that the optimisation problem includes range constraints, it is not possible to use an analytical method such as the well-known closed-form solution provided by Markowitz (1953). A numerical optimisation method is needed in order to maximise the objective function while imposing a number of range constraints. The most appropriate optimisation method to use is a quadratic optimisation process. A quadratic optimisation algorithm is used to maximise forecast portfolio returns, subject to limits on tracking error and short selling. As applying a numerical quadratic method to a large number of stocks can be time consuming, a more efficient approach suggested by Qian, Hua and Sorensen (2007a) is to use an algorithm based on Kuhn-Tucker conditions for optimisation with inequality constraints. The objective function is to maximise portfolio outperformance subject to a limit on tracking error. Additional constraints imposed to create portfolios that fit the active extension structure, that is to ensure that portfolios have 100% net exposure and a limit on the level of short selling (for example 30% for a 130/30 fund).

The objective function for each optimisation is to maximise the information ratio after transaction costs, subject to a number of constraints. A budget constraint of full investment is placed on the portfolio, with additional limits placed on the target level of short selling employed. Risk is controlled by a limit on tracking error, consistent with the construction of optimal portfolios in Qian, Hua and Sorensen (2007a). A summary of portfolio constraints is outlined in Table 6.2. Consistent with Clarke, de Silva and Thorley (2002), we do not incorporate additional size of position or factor exposure constraints.

A practical issue encountered is that the universe of selectable stocks, the constituents of the S&P/ASX 200, varies over time as stocks are added to or removed from the index. Over time, stocks will naturally enter and exit the index for a number of reasons including takeovers, listings, delistings, changes in liquidity, changes in free float or increases/decreases in market value. In total, there have been a total of 376 unique stocks in the S&P/ASX 200 over the eight year period considered in this thesis. To account for this, the stock selection is restricted to only those stocks included in the index on the rebalancing date. If a stock is added to the index, it becomes available for investment. If a stock is removed from the index, any outstanding position long position is sold, or any short position in the stock is bought back. To incorporate this into the model, a restriction is placed on the optimiser that portfolio weights are set to zero if the particular stock is not a constituent of the index as of the balance date.

There may be other constraints that in practice are placed on portfolios, including limits on individual active positions, sector bias, size bias or bias towards value or growth stocks. These constraints are not considered for the optimisation process. Introducing these constraints would require an arbitrary choice of what limits to set and would lower the transfer coefficient by restraining the optimisation process from fully implementing all available information into the portfolio structure. Imposing a tracking error constraint should present a sufficient risk control for the portfolio without resorting to limits on individual positions or limits to factor exposure, such as value-growth neutrality or size-neutrality. This is consistent with Clarke, de Silva and Thorley (2002), who find that additional constraints on position limits or factor exposure are suboptimal as their effect reduces the transfer coefficient.

Table 6.2: Portfolio constraints

Name	Constraint	Description
Budget constraint	$\sum_a w_{p,a} = 1$	To maintain consistency with the structure of active extension portfolios, the portfolio is fully invested at all times.
Short-selling (gross exposure)	$\sum_a \lvert w_{p,a} \rvert \leq 1 + 2\varphi$	Short selling is limited to being less or equal to a target level of short selling by restricting gross exposure; eg for 130/30, phi is equal to 30%, restricting gross exposure to 160%
Tracking error	$\sum_a \sum_b (w_{p,a} - w_{i,a})(w_{p,a} - w_{i,a})\sigma_{a,b}$ $\leq$ *target level*	Forecast tracking error is limited to a maximum target set for the portfolio.
Investable (inclusion in the index)	$w_{p,a}(1 - I_a) = 0 \quad \forall$ a	Portfolio weights are restricted to zero if the stock is not in the S&P/ASX 200 for that month. I_a is equal to one if the stock is included in the index or zero otherwise.

Costs are also factored into the model to reflect their impact on portfolio performance. An approach suggested by Qian, Sorensen and Hua (2007) is to incorporate transaction costs and stock borrowing costs at the portfolio construction stage. The transaction component of the cost function is determined by applying a cost model incorporating commission and spread costs to the change in portfolio weightings. The short position component of the cost model is determined by proportion of the portfolio short sold, multiplied by the assumed cost of borrowing stock. Including the impact of costs into the portfolio construction model allows the portfolio to be optimised net of any costs involved in shorting stocks or rebalancing the portfolio. Repeating this process for each generated vector of forecasts is undertaken to provide a set of portfolios for analysis over different assumptions of manager skill, risk tolerance, trading costs and market conditions.

The inclusion of a cost model in the portfolio construction model is important to give a fair comparison of the performance of active extension funds against long-only portfolios, as they incur a larger implementation cost. The cost function included in the model incorporates transaction costs and costs of borrowing stock. Consistent with Montagu (2007) and anecdotal evidence from market participants, the base case annual stock borrow cost is assumed to be 50bps, which is around 4.2bps on a monthly basis. The transaction cost function used for this study takes the following form:

$$trans.\ cost = commission + \frac{bid\ /\ ask\ spread}{price} + \sigma\sqrt{\frac{V_{Trade}}{250\overline{V}_{Daily}}} \qquad (6.5)$$

This cost function is provided by Grinold and Kahn (2000a) and incorporates both the explicit cost of commissions and market impact costs. The model is based on an inventory model that estimates the average time taken to clear the inventory of a liquidity supplier taking the opposite position in a trade. The model assumes that a return is required to liquidity suppliers in the form of market impact costs to compensate for the immediacy of trading. A portfolio size of $100m is assumed for the purposes of calculating daily volume traded.

This cost function may overstate the cost of trading in three ways. Firstly, it is based on an inventory model where trading is conducted using market orders against existing limit orders or a market maker. In reality, some of the trading may take place by placing limit orders and thus incur a lower cost. Additionally, it assumes that trading takes place in one trading day, however large orders may be broken up over multiple days. The model also assumes that all trades are conducted on market, when in practice large portions of the trade may be able to be conducted off-market without incurring a market impact cost. As a result the model may overstate transaction costs, however considering that one aim of this study is to show that active extension portfolios outperform long-only funds, it is preferable to overstate rather than understate transaction costs.

Portfolios are rebalanced monthly, with the transaction cost function applied based on the rebalancing required to meet the new target weights. This study begins with an analysis of the performance of active extension portfolios, assuming the base case costs, information coefficient and tracking error target. The assumptions are then varied, with the sensitivity to active extension portfolio performance measured. Sensitivity to variations in skill levels, risk constraints and costs are measured by running a series of optimisations with modifications made to the assumptions. Variation with respect to market conditions, cross-sectional dispersion and volatility are measured by performing a regression analysis on the sensitivity of performance of the active extension portfolios to these factors.

Table 6.3: Summary of model base-case assumptions

Name	Assumption	Based on
Information coefficient	0.1	Montagu (2007): 0.09 Kroll (2005): 0.05-0.15
Tracking error limit	4%	Montagu (2007): 4% Liodakis (2007): 1-5% Kroll (2005): 4% Martielli (2005): 5%
Commission costs	0.4%	Anecdotal: 0.4%
Stock borrow costs	0.5%	Montagu (2007): 0.5% White (2007): 0.65% Anecdotal: 0.5%
Funding spread	0.5%	White (2007): 0.5-0.7%

6.5 Performance measurement

The main performance measure used to measure portfolio performance is risk-adjusted performance, measured by the information ratio of the portfolio. Information ratios are defined as excess return over the benchmark, divided by tracking error:

$$IR = \frac{E\left[R_p - R_b\right]}{\sigma\left(R_p - R_b\right)} \tag{6.5}$$

Qian, Hua and Sorensen (2007a) recommend the use of information ratios when comparing long-only managers to active extension managers. For the purposes of this study, it allows for a comparison among portfolios with different levels of shorting against the performance of the benchmark index. Information ratios are also an appropriate measure of performance across portfolios with different tracking errors as their calculation adjusts for different targeted tracking errors. The statistical significance of portfolio outperformance can be analysed using the following t-statistic:

$$t_a = \frac{E\left[R_p - R_b\right]\sqrt{T-1}}{\sigma\left(R_p - R_b\right)} = IR\sqrt{T-1} \tag{6.6}$$

Since the realised information coefficient can be measured, the Clarke, de Silva and Thorley (2002) modified fundamental theory of active management can be used to back out the realised transfer coefficient from performance:

$$TC = \frac{IR}{IC.\sqrt{n}} \tag{6.7}$$

The above metrics provide a means by which portfolio performance can be analysed over different levels of short selling.

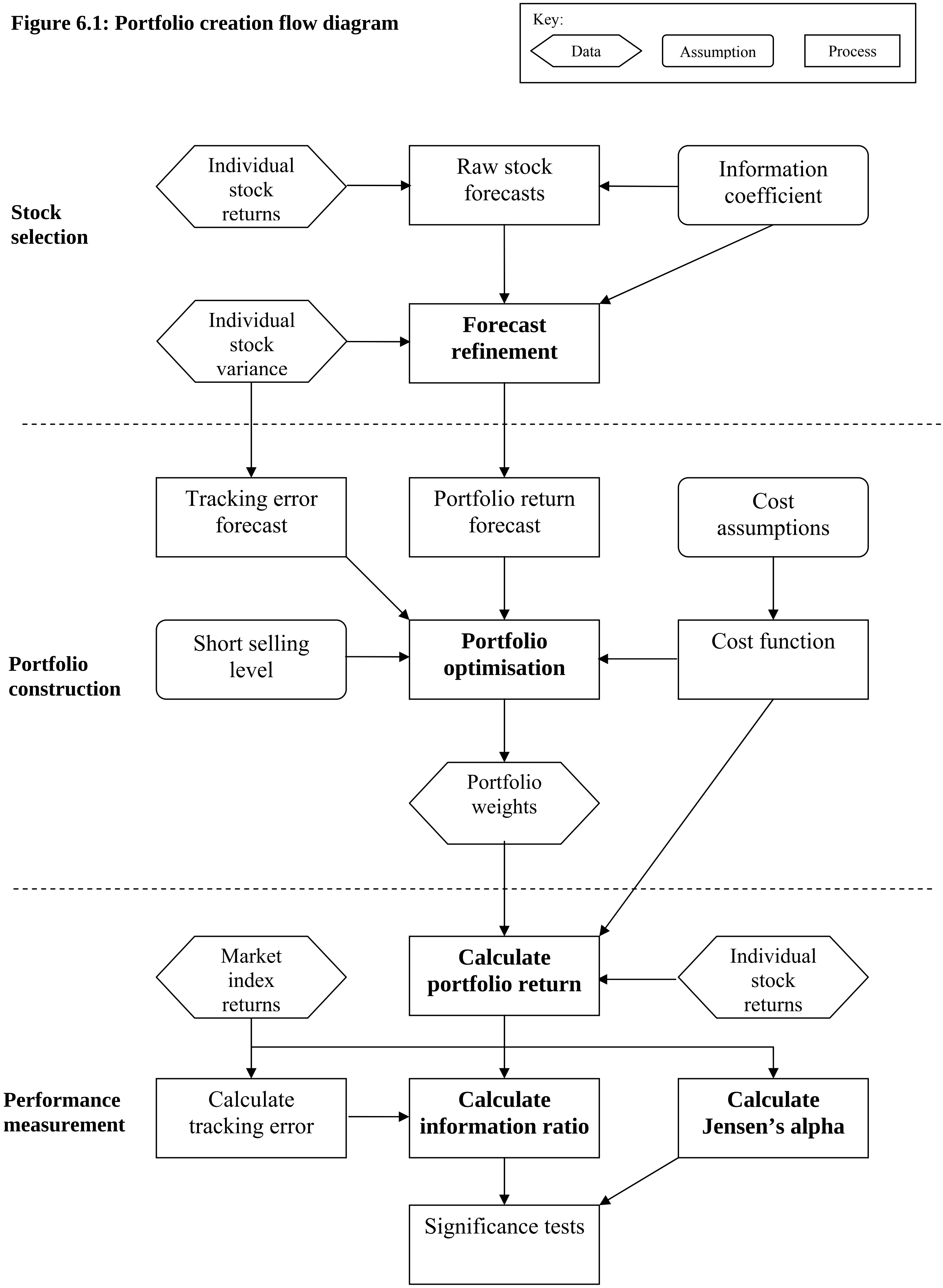
Although information ratios are commonly used through industry and other active extension literature, one potential drawback is that they do not take into account what the net exposure to market risk is. For example, if a portfolio has a beta greater than one, the numerator term of portfolio return less portfolio return will be above zero over the long-term. This is not expected to be a significant issue, as the constructed portfolios are expected to be well diversified and as such will have betas tending towards one. For completeness, the results using information ratios are checked for robustness by adjusting for any differences in betas across portfolios. To achieve this, average measures of alpha are calculated to measure outperformance on a risk-adjusted basis, where risk is measured by beta.

In this context, alpha refers to the excess returns over those predicted by the CAPM equation, as defined by Jensen (1968). Jensen's alpha provides an appropriate measure of performance as the fund remains fully invested with the same risk characteristics relative to the benchmark index for the full period. Alpha and beta for the portfolio are calculated by ordinary least squares on a modified CAPM:

$$R_p - R_f = \alpha + \beta(R_m - R_f) + \varepsilon \tag{6.8}$$

This gives an ex-post measurement of risk-adjusted portfolio outperformance. Portfolio total returns are used, with market returns given by the returns on the S&P/ASX 200 Accumulation index and the risk-free rate given by the 10-year Australian government bond yield. Alpha that is positive at a statistically significant level can be interpreted as outperformance of the index on a risk-adjusted basis. Paired t-tests are also run on alphas for the long-only portfolio against active extension portfolios based on the same set of forecast returns.

Figure 6.1: Portfolio creation flow diagram



7. RESULTS

The following chapter provides a summary of the performance of the simulated active extension portfolios relative to long-only portfolios and the benchmark returns. Performance figures are presented as raw returns, excess returns, information ratios and Jensen's alphas, with tests for statistical significance performed on the latter two. The sensitivity of performance to changes in the endogenous and exogenous factors outlined in the hypotheses is measured, including the effect of different skill levels, costs, volatility, cross-sectional dispersion and market conditions.

7.1 Performance overview

Using the base case assumptions 100 simulated sets of forecasts were created, from which portfolios were constructed at 11 different levels of short selling for a total of 1,100 portfolios, rebalanced monthly. Table 7.1 gives an overview of the performance of the simulated active extension strategies. Over the sample period of May 2000 to July 2008, the active extension portfolios outperformed the equivalent long-only and benchmark index returns by a statistically significant margin. The average compound annual growth rate (CAGR) for 130/30 portfolios was 15.2%, compared with 13.3% for long-only funds utilising the same forecasts. The CAGR for the benchmark S&P/ASX 200 Accumulation index was 10.1%. The performance of active extension portfolios increased with the level of short selling, with 150/50 funds having the highest CAGR of 16.1% compared to the returns for 110/10 of 14.2%. The portfolios with higher levels of short selling had higher information ratios and transfer coefficients, showing that relaxation of the long-only constraint leads to the construction of more efficient portfolios. Using the method of Jensen (1968) to measure outperformance after adjusting for systematic risk, the average portfolio alpha is found to be statistically greater than zero while beta is statistically no different to one.

Table 7.1: Average performance for long-only and active extension funds, using base-case simulation assumptions

This table presents the mean annualised performance for the simulated portfolios over different levels of short selling. Mean excess return, tracking error and information ratio are presented for each set of portfolios. Alpha and beta figures for the median portfolio in terms of performance are also presented. Figures are provided before (gross) and after (net) the involved transaction costs and stock borrow costs. Significance tests for information ratios and Jensen's alphas are run under the null hypothesis that risk-adjusted outperformance is not greater than zero by a statistically significant level. The significance test for beta identifies whether beta is greater or lower than one by a statistically significant margin. Statistical significance at the 5% and 1% level is represented by * and ** respectively.

	100/0	**105/5**	**110/10**	**115/15**	**120/20**	**125/25**	**130/30**	**135/35**	**140/40**	**145/45**	**150/50**
Gross ER	3.63%	4.16%	4.52%	4.74%	4.97%	5.32%	5.61%	6.05%	6.29%	6.42%	6.45%
Gross TE	4.02%	4.04%	4.09%	4.08%	4.14%	4.29%	4.44%	4.60%	4.64%	4.69%	4.72%
Gross IR	**0.90**	**1.03**	**1.10**	**1.16**	**1.20**	**1.24**	**1.26**	**1.32**	**1.36**	**1.37**	**1.37**
Turnover	39%	42%	44%	45%	46%	49%	50%	52%	55%	56%	58%
Trading costs	0.28%	0.29%	0.31%	0.32%	0.33%	0.34%	0.35%	0.37%	0.38%	0.40%	0.41%
Borrow and funding costs	0.00%	0.05%	0.10%	0.15%	0.20%	0.25%	0.30%	0.35%	0.40%	0.45%	0.50%
Total costs	0.28%	0.34%	0.41%	0.47%	0.53%	0.59%	0.65%	0.72%	0.78%	0.85%	0.91%
Net ER	3.35%	3.83%	4.11%	4.27%	4.45%	4.73%	4.96%	5.33%	5.51%	5.57%	5.54%
Net IR	**0.83**	**0.95**	**1.00**	**1.05**	**1.07**	**1.10**	**1.12**	**1.16**	**1.19**	**1.19**	**1.17**
IR t-stat	2.21	2.51*	2.66*	2.77*	2.84*	2.92*	2.96*	3.07*	3.14*	3.14*	3.11*
TC	0.59	0.67	0.71	0.74	0.76	0.78	0.79	0.82	0.84	0.84	0.83
Alpha	**0.0024***	**0.0028****	**0.0077****	**0.0078****	**0.0078****	**0.0082****	**0.0083****	**0.0085****	**0.0088****	**0.0088****	**0.0090****
Beta	1.027	1.014	0.985	0.993	1.023	0.995	1.026	1.032	0.986	1.005	0.967

Table 7.1 shows an increase in the information ratio as the level of short selling is increased, with active extension portfolios utilising higher levels of short selling returning a higher risk-adjusted return. Information ratios are presented both on a pre-costs and post-costs basis. After transaction, stock borrow and funding costs, active extension portfolios are still able to outperform equivalent long-only portfolios despite costs reaching as high as an average 0.91% for 150/50 portfolios. Applying a t-test to the realised information ratios shows that the outperformance for the sampled active extension portfolios at 105/5 and above is significant at a 5% level. Using the notation of Clarke, de Silva and Thorley (2002)[15], the transfer coefficients are able to be calculated from the information coefficient, breadth and realised information ratio. The average transfer coefficient for the long-only portfolios is 0.59, implying that 41% of the theoretical unconstrained information ratio is lost to implementation costs and the effects of constraints. Relaxing the long-only constraints leads to an increase in average transfer coefficient, with the 140/40 and 145/45 portfolios returning the highest average transfer coefficients of 0.84.

Although the ex-ante tracking error target was set to 4%, the ex-post tracking error often exceeds this target by an amount that increases at higher levels of short selling. Qian, Hua and Sorensen (2007a) identify that a variation in IC over time, representing strategy risk, causes realised tracking error to increase above its target level. Although realised tracking error increases as the level of short selling is increased, on a risk-adjusted basis the information ratio is still higher for larger levels of short positions.

An analysis of portfolio performance is also performed using Jensen's alpha as a measure of benchmark outperformance after adjusting for systematic risk exposure. The realised alpha and beta for the portfolio with median performance is shown in table 7.1,

[15] For additional detail see section 4.2.

with statistical significance at the 5% and 1% level denoted by * and ** respectively. The statistical test performed on portfolio alphas tests whether they are greater than zero by a statistically significant amount. The test performed for the portfolio betas is that they are greater than or less than one by a statistically significant amount. The alphas for all active extension portfolios were greater than zero at a 1% level of significance, while none of the betas were significantly different to one at the 5% level. This indicates that, after adjusting for exposure to systematic risk, the active extension portfolios outperformed the benchmark index, with higher levels of short selling corresponding to higher levels of outperformance. Beta was found to statistically be no different to one, which confirms hypothesis seven that active extension portfolios have equal performance whether the overall market has positive or negative returns.

An additional test performed tests alphas for the active extension portfolios against equivalent long-only portfolios. A regression is run on the equation given in equation 6.8 to calculate the alphas for each portfolio. The alphas for portfolios at each level of short selling are tested against the alphas for long-only portfolios. A paired t-test is used to test that the mean difference between alphas in the long-only and active extension portfolios is greater than zero at a statistically significant level. Active extension and long-only portfolios created using the same set of forecasts are paired, such that each pair in the test consists of two portfolios created using the same set of inputs with the only difference being the level of short selling. Table 7.2 presents the results of the paired t-test. All active extension portfolios exhibited higher alphas than the equivalent long-only portfolio. The mean level of alpha for portfolios with a 5% short selling level exceed that of the long-only portfolios with a 10% level of statistical significance, while the active extension portfolios with a level of short selling 10% or above outperformed the long-only portfolios at the 1% level of significance.

Table 7.2: Paired t-test for active extension portfolio alphas

This table shows the results of a paired t-test run between the realised alphas for each pair of long-only and active extension portfolios constructed using the same set of forecasts. T-statistics are presented with corresponding p-values based on a sample size of 100.

	105/5	110/10	115/15	120/20	125/25	130/30	135/35	140/40	145/45	150/50
Mean alpha	0.0026	0.0076	0.0080	0.0081	0.0083	0.0084	0.0085	0.0088	0.0089	0.0092
t-value	1.60	16.35	17.01	16.76	16.84	18.42	18.65	16.92	20.12	20.27
p-value	0.055	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Figure 7.1 shows the average information ratio over different levels of short selling, both before and after costs, and in comparison to the maximum possible information ratio achievable with no constraints or costs (i.e. a transfer coefficient of 1). The greatest jump in performance occurs at the initial relaxation of the short-selling constraint, with the marginal increase in performance decreasing as the level of short selling increases. As the level of short selling is increased, the increased cost drag widens the difference between before costs and after costs measures of information ratio. Despite this, there is still a tangible benefit at a 4% tracking error in increasing the level of short sales past the 130/30 level after accounting for the increase in costs.

Figure 7.1: Average information ratios across short selling levels

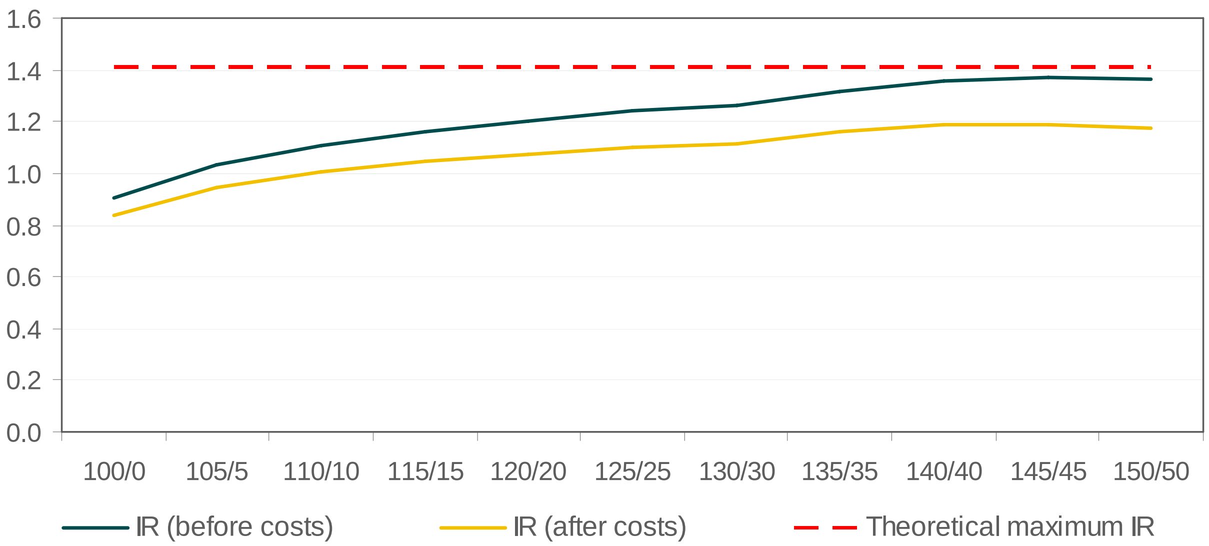
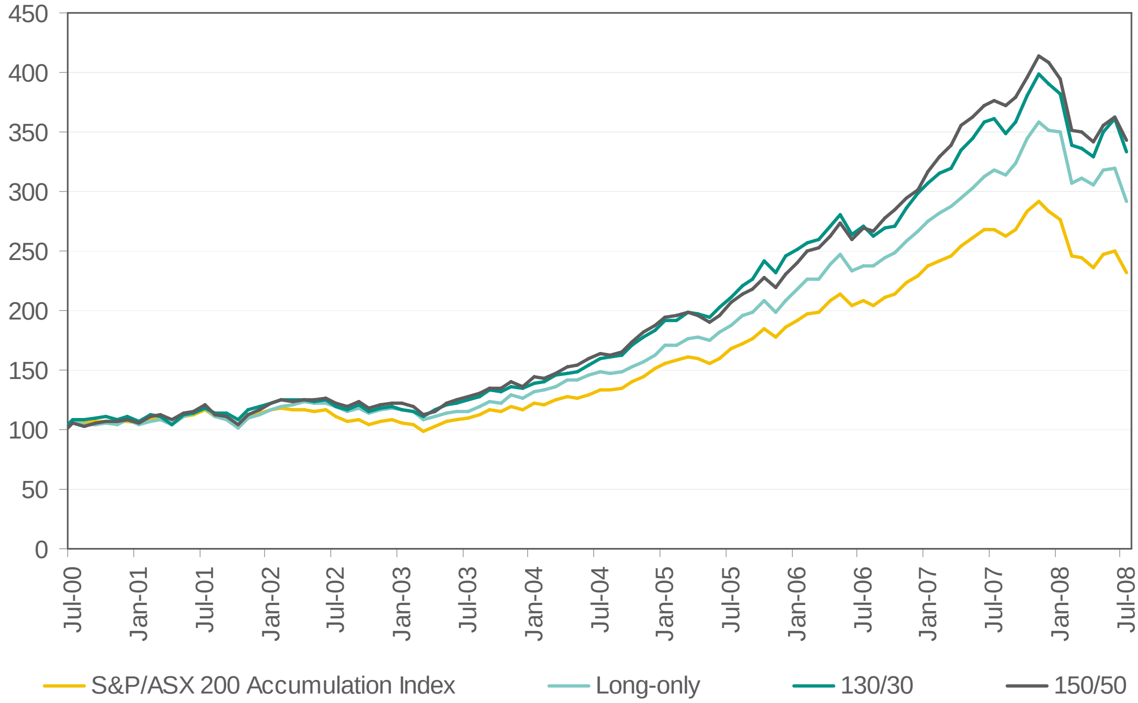


Figure 7.2 shows the average performance over the sample period of long-only, 130/30 and 150/50 strategies against the benchmark S&P/ASX 200 Accumulation index. Each portfolio is rebased to 100 as of the start date. Both long-only and active extension portfolios outperform the benchmark index due to a relatively high assumed information coefficient of 0.1. The active extension portfolios benefit from a relaxation in the long-only constraint and are able to consistently outperform both the long-only portfolios and benchmark index over the sample period.

Figure 7.2: Cumulative performance of long-only and active extension portfolios



7.2 Variation in skill levels

Hypothesis one considers the effect of fund manager skill on the performance of active extension strategies. Intuitively, a manager with no skill will have no benefit from introducing short-selling into their portfolios, as the net effect will be an increase in financing, stock borrow and trading costs. For larger levels of skill, the manager will be able to make more accurate forecasts and will thus be able to benefit more from the introduction of short sale positions. To simulate the effect of different skill levels, portfolios are simulated with information coefficients of 0.05, 0.1 and 0.15 to represent managers with low skill, good skill and exceptional levels of skill.

Table 7.3 provides a summary of the performance for these portfolios. The performance across all short selling levels is highest for the portfolio with the highest information coefficient, reflecting the higher information content in the generated forecasts. However, there is a greater increase in performance for the 'exceptional skill' portfolio in relaxing the long-only constraint than for the 'low skill' portfolio. Figure 7.3 shows this difference graphically, with the information coefficient of the 'exceptional skill' portfolios increasing 65% due to moving from 100/0 to 150/50, while the information coefficient of the 'low skill' portfolio decreases 2% for the same change in short selling. The CAGR for the 'exceptional skill' portfolios increased by from 14.4% for the long-only portfolio to 20.0% for the 150/50 portfolio (+5.6%). By comparison, the 'good skill' portfolios increased from 13.3% to 16.1% (+2.8%), while the 'low skill' portfolios decreased from 14.8% to 14.7% (-0.1%). This confirms hypothesis one, that managers with higher skill levels have a greater increase in performance from relaxing the long-only constraint.

Figure 7.3: Average information ratios across skill levels

Table 7.3: Active extension fund performance across different skill levels

This table presents the mean annualised performance for the simulated portfolios at different levels of short selling and different skill levels. Mean excess returns, tracking errors, information ratios and transfer coefficients are presented for each portfolio, along with computed alphas for the median-performing portfolio. Figures are provided on an after costs basis. Significance tests for information ratios and Jensen's alphas are run under the null hypothesis that risk-adjusted outperformance is not greater than zero by a statistically significant level. Statistical significance at the 5% and 1% levels are represented by * and ** respectively.

	100/0	**105/5**	**110/10**	**115/15**	**120/20**	**125/25**	**130/30**	**135/35**	**140/40**	**145/45**	**150/50**
Low skill (IC = 0.05)											
ER	2.03%	2.18%	2.25%	2.23%	2.31%	2.25%	2.24%	2.33%	2.26%	2.17%	2.26%
TE	3.99%	4.01%	4.03%	4.05%	4.09%	4.19%	4.22%	4.28%	4.31%	4.39%	4.51%
IR	**0.51**	**0.54**	**0.56**	**0.55**	**0.57**	**0.54**	**0.53**	**0.54**	**0.52**	**0.49**	**0.50**
TC	0.72	0.77	0.79	0.78	0.80	0.76	0.75	0.77	0.74	0.70	0.71
Alpha	**0.0014**	**0.0018**	**0.0030***	**0.0041****	**0.0050****	**0.0045****	**0.0048****	**0.0050****	**0.0042****	**0.0044****	**0.0047****
Good skill (IC = 0.10)											
ER	3.35%	3.83%	4.11%	4.27%	4.45%	4.73%	4.96%	5.33%	5.51%	5.57%	5.54%
TE	4.02%	4.04%	4.09%	4.08%	4.14%	4.29%	4.44%	4.60%	4.64%	4.69%	4.72%
IR	**0.83**	**0.95***	**1.00***	**1.05***	**1.07***	**1.10***	**1.12***	**1.16***	**1.19***	**1.19***	**1.17***
TC	0.59	0.67	0.71	0.74	0.76	0.78	0.79	0.82	0.84	0.84	0.83
Alpha	**0.0024***	**0.0028****	**0.0077****	**0.0078****	**0.0078****	**0.0082****	**0.0083****	**0.0085****	**0.0088****	**0.0088****	**0.0090****
Exceptional skill (IC = 0.15)											
ER	4.45%	5.11%	5.32%	5.93%	6.34%	6.77%	7.33%	8.01%	8.61%	8.93%	9.40%
TE	4.03%	4.08%	4.11%	4.17%	4.21%	4.31%	4.49%	4.72%	4.89%	5.01%	5.15%
IR	**1.10***	**1.25***	**1.29***	**1.42****	**1.51****	**1.57****	**1.63****	**1.70****	**1.76****	**1.78****	**1.82****
TC	0.52	0.59	0.61	0.67	0.71	0.74	0.77	0.80	0.83	0.84	0.86
Alpha	**0.0032****	**0.0088****	**0.0089****	**0.0090****	**0.0095****	**0.0103****	**0.0123****	**0.0128****	**0.0137****	**0.0141****	**0.0153****

Hypothesis two considers the effect on performance of a manager who has a skew in performance towards picking long-side or short-side stocks. A manager with skill in managing long-only portfolios may have more skill in identifying securities for the long component of the portfolio than for the short side due to their experience in solely picking long-only stocks. Using the 100 simulated forecasts and associated portfolios created in section 7.1 that assumed a tracking error of 4% and information coefficient of 0.1, an additional two sets of portfolios were created. One set of portfolios simulates a manager with a bias in skill towards identifying outperforming stocks for long positions by giving the manager a skill of 0.15 in selecting stocks that go on to outperform the index, and a skill of 0.05 at selecting underperforming stocks. Similarly, the portfolios that simulate a manager with a bias towards picking short-side positions has an information coefficient of 0.05 for stocks that outperform the index and 0.15 for stocks that underperform the index. Assuming that over the sample period the same number of stocks outperformed and underperformed the index, all three sets of portfolios have an average information coefficient of 0.1.

Table 7.4 shows the results for all three sets of portfolios over the full eight-year period. When the long-only constraint was imposed, the portfolio based on long-biased skill outperformed the equal skill and short-biased skill portfolios. However, at 130/30 and above, the equal skill portfolio outperformed the portfolios with bias in skill. The portfolios constructed with long-biased and short-biased skill underperformed the equal skill portfolio at levels of short selling above 130/30. In addition, all active extension portfolios at shorting levels of 120/20 and above across the different skill classifications were able to outperform all the long-only portfolios.

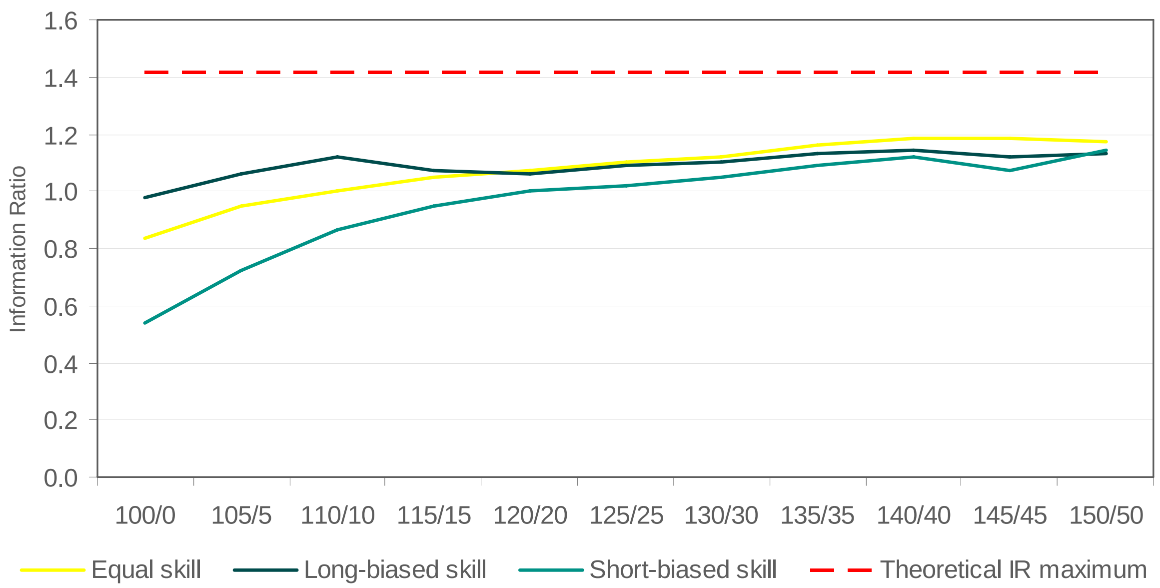
Table 7.4: Performance for active extension funds with bias in stock-selection ability

This table presents the mean annualised performance for the simulated portfolios, where stock selection skill is skewed towards picking potential outperformers or potential underperformers. Mean excess return, tracking error and information ratio are presented for each portfolio, along with alphas for the median-performing portfolio. Figures are provided after costs. Significance tests for information ratios and Jensen's alphas are run under the null hypothesis that risk-adjusted outperformance is not greater than zero by a statistically significant level. Statistical significance at the 5% and 1% level is represented by * and ** respectively.

	100/0	**105/5**	**110/10**	**115/15**	**120/20**	**125/25**	**130/30**	**135/35**	**140/40**	**145/45**	**150/50**
Equal skill											
ER	3.35%	3.83%	4.11%	4.27%	4.45%	4.73%	4.96%	5.33%	5.51%	5.57%	5.54%
TE	4.02%	4.04%	4.09%	4.08%	4.14%	4.29%	4.44%	4.60%	4.64%	4.69%	4.72%
IR	**0.83**	**0.95***	**1.00***	**1.05***	**1.07***	**1.10***	**1.12***	**1.16***	**1.19***	**1.19***	**1.17***
TC	0.59	0.67	0.71	0.74	0.76	0.78	0.79	0.82	0.84	0.84	0.83
Alpha	**0.0024***	**0.0028****	**0.0077****	**0.0078****	**0.0078****	**0.0082****	**0.0083****	**0.0085****	**0.0088****	**0.0088****	**0.0090****
Long-biased skill											
ER	3.94%	4.26%	4.60%	4.46%	4.39%	4.91%	4.86%	5.31%	5.41%	5.26%	5.42%
TE	4.04%	4.02%	4.12%	4.15%	4.14%	4.51%	4.41%	4.69%	4.72%	4.71%	4.79%
IR	**0.98***	**1.06***	**1.12***	**1.07***	**1.06***	**1.09***	**1.10***	**1.13***	**1.15***	**1.12***	**1.13***
TC	0.69	0.75	0.79	0.76	0.75	0.77	0.78	0.80	0.81	0.79	0.80
Alpha	**0.0035****	**0.0079****	**0.0088****	**0.0086****	**0.0081****	**0.0073****	**0.0075****	**0.0082****	**0.0079****	**0.0095****	**0.0083****
Short-biased skill											
ER	2.17%	2.94%	3.51%	3.95%	4.40%	4.52%	4.63%	5.06%	5.25%	5.04%	5.45%
TE	4.03%	4.08%	4.07%	4.17%	4.38%	4.44%	4.42%	4.65%	4.70%	4.69%	4.76%
IR	**0.54**	**0.72**	**0.86**	**0.95***	**1.00***	**1.02***	**1.05***	**1.09***	**1.12***	**1.07***	**1.15***
TC	0.38	0.51	0.61	0.67	0.71	0.72	0.74	0.77	0.79	0.76	0.81
Alpha	**0.0019***	**0.0021***	**0.003****	**0.0055****	**0.0070****	**0.0069****	**0.0085****	**0.0087****	**0.0089****	**0.009****	**0.0088****

Figure 7.4 shows how the skew in skill affects the information ratios of active extension strategies. With no short-selling (100/0), the portfolio with long-biased skill showed the greatest level of performance. The peak level of performance for the portfolios with long-biased skill was at a level of 110/10, with little discernable increase in performance above this level. This is consistent with Liodakis (2007), who proposes that there will be some limited benefit to introducing short selling despite little skill in picking potential underperformers. The portfolio with short-biased skill showed the lowest information ratio with the no short-selling constraint imposed, but had the greatest increase in performance from the relaxation of the long-only constraint. The equal skill portfolio had performance roughly in between the long-biased and short-biased skill portfolios for low levels of short selling. At a 120/20 level and above, the equal skill portfolio outperformed the long-biased and short-biased skilled portfolios. This is not consistent with hypothesis two, as the portfolios with long-biased skill and equal skill are able to outperform the portfolios with short-biased skill at all levels of short selling.

Figure 7.4: Average information ratios across manager skill biases

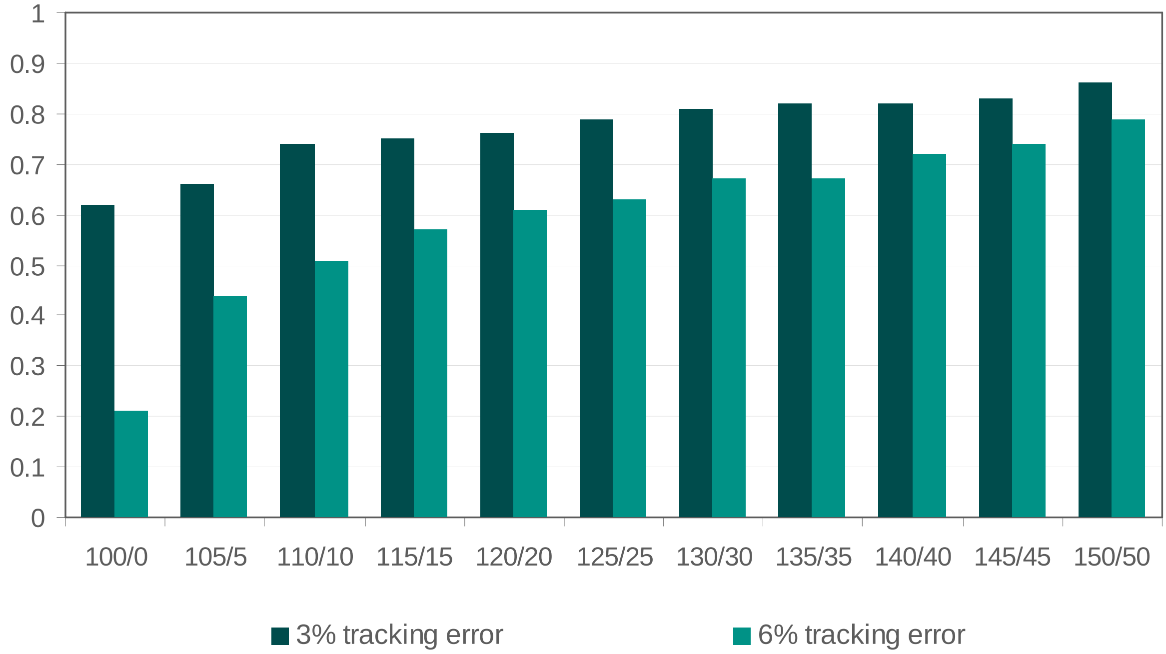


7.3 Risk constraints

Hypothesis three considers the effects of risk constraints on the performance of active extension strategies over an equivalent long-only strategy. A higher level of tracking error implies that larger active positions are taken in the portfolio, which increases the restrictiveness of the long-only constraint. As a result, portfolios with higher tracking error are likely to benefit more from introducing short selling than portfolios with lower tracking error. 100 sets of forecasts were simulated, with long-only portfolios and active extension portfolios constructed over 11 different levels of short selling at 5% intervals with five different levels of tracking error, creating a total sample of 5,500 portfolios that are rebalanced monthly.

Table 7.5 shows the average information ratios and transfer coefficients for the sampled portfolios across different levels of tracking error. The largest excess returns were for the portfolios with higher tracking error and higher levels of short selling, as these portfolios allowed the largest active positions to be taken to reflect the forecast stock returns. The increase in average information ratio from long-only to 150/50 can be seen to be positively related to the level of tracking error in the portfolio. At a 2% level of tracking error, the average information ratio increases from 0.98 for the long-only portfolio to 1.20 for the 150/50 fund (+23%). At the 6% level of tracking error, the average information ratio increases from 0.3 to 1.12 (+273%). This result is consistent with hypothesis 7, which states that the performance increase from relaxing the long-only constraint is highest for portfolios with greater levels of tracking error. Figure 7.5 also shows the difference in transfer coefficients over portfolios with different target levels of tracking error.

Figure 7.5: Transfer coefficients for active extension portfolios



The highest information ratios and transfer coefficients were found to be for the portfolios with the lowest tracking error, although there was a comparatively smaller increase in performance for introducing short positions, and a negligible performance benefit in increasing the level of short selling past 30%. As the level of short selling is set as a maximum upper bound, for many portfolios with a short selling level above 30% the portfolio optimiser chose to use a smaller level of short selling than the maximum in order to maximum returns within the relatively low tracking error. There would be little benefit in constraining these portfolios into an exact 50% shorting level, as this would be difficult to achieve within the 2% tracking error limit. As a result, there is little benefit to increasing short selling in these portfolios past the typical 30% level as imposing a high level of short selling is needlessly restrictive.

Table 7.5: Average performance for long-only and active extension funds with different tracking error targets

This table shows the mean excess returns, tracking errors, information ratios and transfer coefficients for each level of tracking error for a given level of short selling. Risk-adjusted outperformance, as measured by the information ratio, is higher for portfolios with lower levels of tracking error and higher levels of short selling. Significance tests are performed on the information ratios, with * and ** denoting significance levels of 10% and 5% respectively.

	100/0	**105/5**	**110/10**	**115/15**	**120/20**	**125/25**	**130/30**	**135/35**	**140/40**	**145/45**	**150/50**
2% target tracking error											
ER	1.96%	2.14%	2.24%	2.30%	2.46%	2.51%	2.65%	2.58%	2.65%	2.61%	2.63%
TE	2.01%	2.02%	2.06%	2.06%	2.10%	2.11%	2.13%	2.15%	2.18%	2.20%	2.19%
IR	**0.98****	**1.06****	**1.09****	**1.12****	**1.17****	**1.19****	**1.24****	**1.20****	**1.22****	**1.19****	**1.20****
TC	**0.69**	**0.75**	**0.77**	**0.79**	**0.83**	**0.84**	**0.88**	**0.85**	**0.86**	**0.84**	**0.85**
3% target tracking error											
ER	2.64%	2.83%	3.22%	3.26%	3.35%	3.58%	3.76%	3.91%	3.95%	4.04%	4.20%
TE	3.02%	3.03%	3.08%	3.07%	3.12%	3.20%	3.29%	3.38%	3.41%	3.45%	3.46%
IR	**0.88***	**0.93****	**1.05****	**1.06****	**1.07****	**1.12****	**1.15****	**1.16****	**1.16****	**1.17****	**1.22****
TC	**0.62**	**0.66**	**0.74**	**0.75**	**0.76**	**0.79**	**0.81**	**0.82**	**0.82**	**0.83**	**0.86**
4% target tracking error											
ER	3.35%	3.83%	4.11%	4.27%	4.45%	4.73%	4.96%	5.33%	5.51%	5.57%	5.54%
TE	4.02%	4.04%	4.09%	4.08%	4.14%	4.29%	4.44%	4.60%	4.64%	4.69%	4.72%
IR	**0.83***	**0.95****	**1.00****	**1.05****	**1.07****	**1.10****	**1.12****	**1.16****	**1.19****	**1.19****	**1.17****
TC	**0.59**	**0.67**	**0.71**	**0.74**	**0.76**	**0.78**	**0.79**	**0.82**	**0.84**	**0.84**	**0.83**
5% target tracking error											
ER	2.41%	3.22%	4.13%	4.39%	4.66%	4.86%	5.21%	5.63%	5.83%	6.06%	6.30%
TE	5.02%	5.06%	5.13%	5.09%	5.15%	5.29%	5.42%	5.60%	5.65%	5.72%	5.71%
IR	**0.48**	**0.64**	**0.81***	**0.86***	**0.91****	**0.92****	**0.96****	**1.00****	**1.03****	**1.06****	**1.10****
TC	**0.34**	**0.45**	**0.57**	**0.61**	**0.64**	**0.65**	**0.68**	**0.71**	**0.73**	**0.75**	**0.78**
6% target tracking error											
ER	1.79%	3.77%	4.45%	4.96%	5.40%	5.74%	6.28%	6.47%	7.03%	7.30%	7.85%
TE	6.03%	6.07%	6.17%	6.15%	6.26%	6.44%	6.63%	6.83%	6.90%	6.98%	7.03%
IR	**0.30**	**0.62**	**0.72***	**0.81***	**0.86***	**0.89***	**0.95****	**0.95****	**1.02****	**1.05****	**1.12****
TC	**0.21**	**0.44**	**0.51**	**0.57**	**0.61**	**0.63**	**0.67**	**0.67**	**0.72**	**0.74**	**0.79**

7.4 Costs

Hypothesis four considers the impact of costs on the performance of active extension strategies. Active extension strategies face additional costs over long-only portfolios through increased turnover, the requirement to pay stock borrow costs on short positions and the financing costs required to pay for the additional long positions. To model the effect of costs, portfolios are simulated at a low, medium and high level of costs. The cost assumptions used are outlined in Table 7.6. 100 simulated portfolios are created for each cost assumption case at each level of short selling, yielding a total 3,300 sample portfolios that are rebalanced monthly over the sample period. The 'base case' cost assumptions are identical to those used for testing all other hypotheses.

Table 7.6: Simulation cost assumptions

	Low	**Medium (base case)**	**High**
Commission costs	0.20%	0.40%	0.60%
Stock borrow costs	0.25%	0.50%	0.75%
Funding spread	0.25%	0.50%	0.75%

Table 7.7 shows the average realised performance and costs for the sampled portfolios. As the portfolio construction process takes into account the effect of costs during the optimisation process, the portfolios have different weightings and therefore different levels of performance before costs. After costs, the portfolios with higher costs have a lower level of performance. The portfolios with the highest costs exhibited the largest drop-off in information coefficient as the level of short selling was increased. The highest information coefficient for the 'high costs' portfolios was 130/30, above which the information coefficient dropped due to the higher trading and borrow costs. The

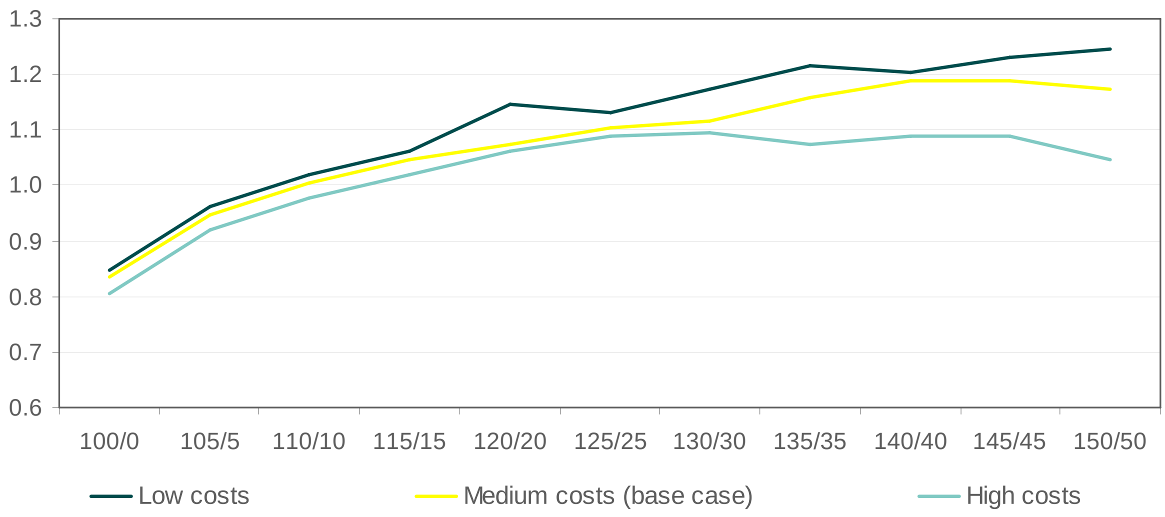
Table 7.7: Sensitivity of active extension performance to changes in trading, borrow and funding costs

This table presents the mean annualised performance for the simulated portfolios over different levels of short selling over the three cost cases outlined in table 7.6. Mean excess returns, tracking errors, information ratios and transfer coefficients are presented for each set of portfolios. Performance figures are provided after the involved transaction costs and stock borrow costs. Significance tests for information ratios are run under the null hypothesis that risk-adjusted outperformance is not greater than zero by a statistically significant level. Statistical significance at the 10% and 5% level is represented by * and ** respectively.

	100/0	**105/5**	**110/10**	**115/15**	**120/20**	**125/25**	**130/30**	**135/35**	**140/40**	**145/45**	**150/50**
Low costs											
Turnover	47%	51%	53%	54%	56%	59%	61%	63%	66%	68%	74%
Trading costs	0.27%	0.28%	0.30%	0.31%	0.32%	0.33%	0.34%	0.36%	0.36%	0.39%	0.42%
Borrow & funding costs	0.00%	0.03%	0.05%	0.08%	0.10%	0.13%	0.15%	0.18%	0.20%	0.23%	0.25%
Total costs	**0.27%**	**0.31%**	**0.35%**	**0.38%**	**0.42%**	**0.45%**	**0.49%**	**0.53%**	**0.56%**	**0.61%**	**0.67%**
ER	3.40%	3.89%	4.16%	4.34%	4.75%	4.84%	5.22%	5.61%	5.54%	5.82%	5.90%
TE	4.01%	4.05%	4.09%	4.09%	4.15%	4.28%	4.45%	4.61%	4.61%	4.73%	4.74%
IR	**0.85***	**0.96****	**1.02****	**1.06****	**1.15****	**1.13****	**1.17****	**1.22****	**1.20****	**1.23****	**1.24****
TC	0.60	0.68	0.72	0.75	0.81	0.8	0.83	0.86	0.85	0.87	0.88
Medium costs (base case)											
Turnover	39%	42%	44%	45%	46%	49%	50%	52%	55%	56%	58%
Trading costs	0.28%	0.29%	0.31%	0.32%	0.33%	0.34%	0.35%	0.37%	0.38%	0.40%	0.41%
Borrow & funding costs	0.00%	0.05%	0.10%	0.15%	0.20%	0.25%	0.30%	0.35%	0.40%	0.45%	0.50%
Total costs	**0.28%**	**0.34%**	**0.41%**	**0.47%**	**0.53%**	**0.59%**	**0.65%**	**0.72%**	**0.78%**	**0.85%**	**0.91%**
ER	3.35%	3.83%	4.11%	4.27%	4.45%	4.73%	4.96%	5.33%	5.51%	5.57%	5.54%
TE	4.02%	4.04%	4.09%	4.08%	4.14%	4.29%	4.44%	4.60%	4.64%	4.69%	4.72%
IR	**0.83***	**0.95****	**1.00****	**1.05****	**1.07****	**1.10****	**1.12****	**1.16****	**1.19****	**1.19****	**1.17****
TC	0.59	0.67	0.71	0.74	0.76	0.78	0.79	0.82	0.84	0.84	0.83
High costs											
Turnover	35%	37%	39%	40%	43%	42%	46%	49%	51%	53%	57%
Trading costs	0.28%	0.29%	0.31%	0.32%	0.33%	0.34%	0.35%	0.37%	0.38%	0.40%	0.41%
Borrow & funding costs	0.00%	0.08%	0.15%	0.23%	0.30%	0.38%	0.45%	0.53%	0.60%	0.68%	0.75%
Total costs	**0.28%**	**0.36%**	**0.46%**	**0.54%**	**0.63%**	**0.72%**	**0.80%**	**0.89%**	**0.98%**	**1.07%**	**1.16%**
ER	3.24%	3.71%	3.99%	4.16%	4.39%	4.66%	4.86%	4.96%	5.05%	5.12%	4.97%
TE	4.02%	4.04%	4.09%	4.09%	4.14%	4.28%	4.44%	4.62%	4.64%	4.70%	4.75%
IR	**0.81***	**0.92***	**0.98****	**1.02****	**1.06****	**1.09****	**1.10****	**1.07****	**1.09****	**1.09****	**1.05****
TC	0.57	0.65	0.69	0.72	0.75	0.77	0.775	0.76	0.77	0.77	0.74

‘low costs’ portfolio suffers less of a drop-off in performance at higher levels of short selling as the cost drag from increased turnover and borrowing is lower. Figure 7.6 graphically shows the information ratios for each set of cost assumptions over different levels of short selling.

Figure 7.6: Average information ratios over different cost assumptions



The important implication from this is that increased costs lower the amount of short selling that should be used, as adding additional short positions beyond a certain point will be inefficient due to the higher costs involved. This implies that, all other factors being equal, higher costs necessitate targeting a lower level of short selling. These results are consistent with hypothesis four, which states that an increase in transaction costs and stock borrow costs lowers the performance of active extension strategies.

7.5 Volatility, cross-sectional spread and market conditions

Hypotheses five, six and seven consider the effect of exogenous market factors on the performance of active extension portfolios. Hypothesis five proposes that the performance of active extension strategies will be greater in periods of higher market volatility due to diversification effects. Hypothesis six looks at the effect of cross-sectional dispersion. As the long-only constraint presents a greater restriction on when stocks are more highly correlated, hypothesis six proposes that active extension portfolios perform better in comparison to long-only portfolios in periods where individual stocks are more highly correlated. Hypothesis seven considers the performance of active extension portfolios in periods where market returns are above or below average. These hypotheses are tested jointly by adding proxies for volatility and cross-sectional dispersion into the CAPM-based equation given in equation 6.8:

$$R_p - R_f = \alpha + \beta_1(R_m - R_f) + \beta_2\sigma_M + \beta_3\rho_M + \varepsilon \qquad (7.1)$$

Equation 7.1 is an extension of Jensen's model (1968) to measure the effect on performance of active extension portfolios of market-wide volatility and cross-sectional dispersion, after adjusting for market returns. Monthly returns from the 100 simulated 130/30 portfolios in section 7.1 are used, for a total sample size of 9,900 observed monthly returns. The measure of cross-sectional dispersion used is the mean pairwise correlation of monthly returns. Volatility for the S&P/ASX 200 Accumulation index was measured on a historical 12-month basis. Table 7.8 shows the results of the above regression.

Table 7.8: Regression results

This table presents the results of the regression outlined in section 7.5. Monthly excess returns over the risk-free rate (10-year bond yield) are regressed against market excess returns, market volatility and pairwise correlations.

Variable	Coefficients	Standard Error	T Statistic	P-value
Intercept	0.000	0.000	-1.449	0.147
Market returns	1.015	0.002	432.230	0.000
Market volatility	-0.357	0.198	-1.802	0.071
Pairwise correl.	0.000	0.001	0.005	0.996

Regression Statistics	
R Square	0.950
Adj.R Square	0.950
Standard Error	0.008
F-statistic	62665
Observations	9900

Table 7.8 displays the regression results which show the explanatory power of market volatility and cross-sectional dispersion on portfolio performance. The coefficient for market volatility was -0.357, suggesting that monthly outperformance decreases by -0.357% for every 1% increase in 12-month rolling market volatility. This is contrary to hypothesis five, which put forward that higher market volatility would lead to higher risk-adjusted portfolio performance. The coefficient for pairwise correlation was close to zero with no statistical significance, implying that pairwise correlation has no effect on the performance of active extension portfolios.

The observed coefficient for beta was 1.015, which is statistically greater than one with a p-value less than 1%. This would suggest that the active extension portfolios outperform the index when index returns are positive and underperform the index when index returns are negative. However, the beta coefficient of 1.015 is only marginally greater than one, implying that the exposure to systematic risk is roughly in line with the benchmark index. This result is also confirmed by the regression testing shown in

Table 7.1, which found that the beta for the active extension portfolios was statistically no different to one.

7.6 Summary of results

Overall, the active extension portfolios simulated in this study outperformed both the equivalent long-only portfolios and the benchmark index, with higher levels of short selling corresponding to increased outperformance. An increase in stock selection skill led to a greater performance increase at the higher levels of short selling, reflecting that the active extension strategy allows for a more efficient implementation of information than a long-only portfolio. The active extension strategy was shown to work best when managers have an equal bias towards identifying potential outperformers or underperformers. The increase in performance from relaxing the long-only constraint was greatest for the portfolios with the highest tracking error, reflecting that portfolios with larger active positions are more likely to be restricted by the long-only constraint. Costs also had a large impact on performance, with higher cost levels having a relatively larger impact at greater levels of short selling due to the higher gross exposure of the portfolio. Cross-sectional spread and market direction had no discernable impact on the performance of active extension strategies, while volatility had the opposite effect to that which was hypothesised. Finally, there was no observable effect of whether active extension portfolios performed better in ‘bull’ or ‘bear’ markets, as beta for the portfolios could not be shown to be statistically different from one.

Table 7.9: Active extension hypotheses

This table summarises the hypotheses outlined in chapter 5 and their subsequent results.

Hypothesis	**Results**
H_1: Managers with higher skill levels have a greater increase in performance from relaxing the long-only constraint.	Confirm
H_2: Managers with a higher skew towards picking underperforming stocks can construct active extension portfolios with higher levels of performance.	Reject
H_3: Portfolios with higher tracking error limits have a greater performance increase from relaxing the long-only constraint.	Confirm
H_4: An increase in transaction costs and stock borrow costs will lower the performance of active extension strategies.	Confirm
H_5: Higher market volatility will increase the performance of active extension strategies.	Reject
H_6: A lower cross-sectional spread of returns will increase the benefits from implementing active extension portfolios.	Cannot confirm
H_7: The level of outperformance or underperformance of active extension portfolios is equivalent across periods of positive or negative market returns.	Confirm

8. CONCLUSION

This dissertation studies the performance of equity portfolios using active extension strategies. The primary difference in active extension funds over long-only funds is the relaxation of the long-only constraint. The main implication of this study is that active extension strategies are the optimal choice for investors who seek actively managed equity portfolios that are fully invested in the market. Active extension portfolios provide an effective blend of long-only funds and market-neutral hedge funds, allowing managers to pursue short-selling opportunities to potentially increase portfolio alpha while simultaneously retaining an exposure to overall market returns. This dissertation has found that active extension portfolios are able to outperform equivalent long-only portfolios and the benchmark index by a statistically significant margin. These results build on previous literature (Qian, Sorensen and Hua, 2007b; Clarke, de Silva and Thorley, 2008) by extending the analysis to encompass a different market and examine the effects of additional variables on performance. These results also have implications for institutional fund managers who are considering offering or investing in active extension strategies.

The degree to which an active extension portfolio outperforms an equivalent long-only portfolio and the benchmark index is positively related to the level of manager skill and negatively related to the level of costs. Active extension strategies do not add additional information, but provide managers with the ability to more efficiently use their existing information. Costs have a significant effect on portfolio performance as they tend to increase as the level of short selling in the portfolio is increased. Whether active extension portfolios are able to outperform long-only portfolios depends on whether the forecasting ability of the manager is sufficient to outperform the cost drag. Provided that the manager has some reasonable degree of forecasting ability, active extension portfolios outperform equivalent portfolios with the long-only constraint in place. If the manager has little or no skill in stock picking, the net effect of using an active extension strategy will be a decrease in performance from the increased cost drag.

The performance of active extension strategies is closely related to the targeted level of risk. Funds with lower risk targets benefit little from introducing short-selling, while for funds with higher risk targets active extension portfolios generally present greater risk/return opportunities than funds concentrated in a small number of long positions. External market conditions such as volatility, pairwise correlation between individual stocks and market direction are found to have a limited impact on active extension performance.

The results of this study have implications for investors seeking to identify whether allocating assets to an active extension fund is appropriate and if so, what characteristics to consider when choosing a fund. Many active extension strategies have only been created in the past five to ten years, which creates difficulties in assessing what future performance of the fund might be. When choosing a fund the manager of the active extension fund must be able to generate outperformance, as if the manager has no skill in adding value the net effect of moving to a short-extension strategy will be negative due to the increased cost burden. It is also preferable for the manager to have experience with shorting. Where the manager is using an active extension strategy, the level of shorting used should also reflect the manager's skill level, risk target, costs and market conditions.

Although this thesis has aimed to be comprehensive in its analysis of the factors driving active extension fund performance, there are still significant avenues for future research.

Testing over a longer period would allow for a more robust analysis of the performance of active extension funds. Applying this analysis to different regions would also confirm whether the results of this thesis apply across different equity markets. The ultimate test of the benefits of active extension funds will be an analysis of their historical performance. At present, given the recent genesis of these strategies there is little in the way of historical performance to compare against long-only funds and index benchmarks. However once longer periods of data are available it will be possible to give a more concrete view on the performance of active extension funds.

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