# THE INFLUENCE OF TIME, SEASONALITY AND MARKET STATE ON MOMENTUM: INSIGHTS FROM THE AUSTRALIAN STOCK MARKET

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**Abstract**

This paper provides further insights into the properties of momentum trading strategies using information from the Australian market. Based on a methodology that avoids the look-ahead bias of many momentum studies that employ monthly data, we confirm the existence of a momentum effect in Australia. In contrast to previously reported results, momentum is stronger amongst larger firms in the Australian market and buying 'winners' generates higher returns than shorting 'losers'. We find strong seasonal influences which are consistent with the tax selling hypothesis and institutional 'window dressing'. In addition, we show that momentum returns are highly variable over time. Specifically the momentum strategies employed in the late 1990s generate higher returns than those in the early 1990s. Some aspects of the effect are quite different from those previously observed in other markets and this is useful for testing theories about the causes of momentum out of sample. We use information on the inter-temporal performance of 'winners' and 'losers' in different market states to determine which of a number of behavioral theories are most predictive of the observed movements of the Australian market. The evidence indicates that models based on the disposition effect better fit the observed data than models based on an overreaction bias.



**Keywords:** Momentum; Seasonality; Australian stock market.

**JEL Classifications** G10, G12, G14

## 1. Introduction

There is a considerable and growing body of literature that deals with cross-sectional momentum in stock returns. Given that it sits uneasily within the paradigm of market efficiency, both the existence and causes of the momentum effect have been subject to extensive investigation. Starting with the seminal paper by Jegadeesh and Titman (1993) the presence of the momentum effect has been extensively documented in the US. Fama and French (1996) suggest that out of sample tests of momentum strategies on international data are desirable to establish whether the US evidence is a result of data snooping. Many studies of this nature have indeed been performed confirming that the effect can be observed in a variety of settings. A number of explanations have been put forward. In broad terms, some studies have investigated whether the effect can be brought within the efficient market paradigm by showing that it represents a rational response to risk factors. Explaining the effect in these terms has proved difficult and many papers have suggested explanations based on various behavioral biases.

The current study extends the literature by providing further insights into the momentum effect using data from the Australian market. Our objective is to go beyond simply assessing whether the effect can be observed out of sample, although this has been a matter of some controversy in the Australian case.[1] The most important objective of the paper is to take advantage of important features of our data and use aspects of the effect that are different from those previously observed in other markets, such as the inter-temporal performance of 'winners' and 'losers' in different market states, to determine which of a number of behavioral theories are most predictive of the observed movements of the Australian market.

We examine the return to a momentum trader who applies a practical trading rule in the Australian market over the period 1991 to 2002. The methodology employed is consistent with Jegadeesh and Titman (1993) with one notable innovation. Instead of using monthly data, daily data are employed to ensure that the actual purchase and sales price is achievable without a look-ahead bias. Although we confirm the existence of a momentum effect, our results show that the return predictability which exists in Australia is qualitatively different in some key respects from that reported in the US and other international markets. Contrary to US findings, the effect is stronger amongst larger stocks in Australia. In addition, price continuation is stronger amongst the losers in the US while it is stronger amongst winners in Australia. Seasonal effects (eg, Jegadeesh and Titman, 1993 and Sias, 2007) are also investigated in the current work. We find strong seasonal

[1] The Australian market has previously been examined by Rouwenhorst (1999), Hurn and Pavlov (2003), Demir et al. (2004) and Durand et al. (2006). In broad terms, the first three of these studies have confirmed that a momentum type effect is exhibited in the Australian market although the study of Durand et al has raised some doubts about this conclusion.

effects which appear to be influenced by the institutional features of both the Australian and US markets.

The stability of the results is also examined by partitioning the data into two time periods. Specifically, it was found that the momentum trading strategies employed over the period 1991-1996 generated lower returns than those employed in the late 1990s. The relatively poorer performance in the earlier time period is largely due to strong price reversals in the loser stocks. One possible explanation for this could be the fact that the market was generally rising in the late 1990s compared to the early 1990s. Accordingly, this observation motivates further tests of the hypothesis, put forward by Cooper et al (2004), that market conditions can affect the performance of momentum trading strategies. The analysis reveals that the momentum strategies do perform better after a rising market and the difference in performance is again largely related to the reversals of losers after a decreasing market. However, this only affects momentum strategies with short holding periods. The asymmetric effect of market states on the performance of winners and losers does lend some support to the behavioral model of Grinblatt and Han (2005). In that model, investors suffer from a 'disposition' effect and tend to sell winners early and hold on to losers for too long. One implication of this model is that following rising (falling) markets, there would be more (less) selling pressure on winners (losers).

The remainder of this paper is organized as follows: Section 2 presents an overview of the relevant empirical and theoretical literature. Section 3 describes the methodology employed to test the profitability of momentum trading strategies in Australia. Section 4 provides an analysis of the empirical findings and finally Section 5 concludes the paper.

## 2. Literature Review

### 2.1 General Evidence

Using data from the NYSE and AMEX, 1965 to 1989, Jegadeesh and Titman (1993, 1995) report that firms with the highest return over the past 3-12 months subsequently outperform firms with the lowest return over the same period. For example a 6x6 strategy (that is, a six-month formation period followed by a six-month holding period) yielded a return of 1.74% per month. In addition the authors found that the momentum profit could not be explained by systematic differences in risk or size.

Using NYSE, AMEX and NASDAQ stock data, 1977 to 1993, Chan, Jegadeesh and Lakhonishiok (1996) found that the momentum effect is distinct from the previously documented post earnings announcement drift although a large proportion of the momentum effect returns are realized in the time window surrounding earnings announcements. Profits to both strategies are robust to the Fama and French (1993) 3-factor model.

A number of papers have reported seasonality in momentum returns. Jegadeesh and Titman (2001) report that the basic momentum strategy exhibits a pattern of seasonality in the month of January. Specifically, they showed that the strategy lost 1.55% in January while making positive returns in every other month. Grinblatt and Moskowitz (2004) argue that momentum profits are higher than average in December at least partially because of tax-loss selling. Sias (2007) reports that momentum profits are considerably higher in quarter ending months, particularly December, and argues that this is due to window dressing by institutional investors and tax loss selling.

The momentum effect is widely investigated in markets outside of the US to address the issues of data snooping. Rouwenhorst (1998) examined the momentum strategy in 12 different European countries.[2] He found that the risk-adjusted abnormal returns of the strategy exceeded 1% per month and the overall results were consistent with Jegadeesh and Titman (1993). Rouwenhorst (1999), Chui Titman and Wei (2000) and Hameed and Yuanto (2001) also document momentum returns in Asian markets. For example, Hameed and Yuanto (2001) found that momentum profits in emerging Asian markets are smaller than those reported in developed countries.[3]

Hon and Tonks (2003) found the momentum strategy to also generate abnormal returns when applied to stocks listed on the London Stock Exchange (1955-1996). Liu, Strong and Xu (1999) examined the profitability of UK momentum strategies for the period 1977 to 1998 and found significant positive returns. Chan, Hameed and Tong (2000) investigate momentum strategies for the stock market indices of 23 countries and find evidence of momentum profits which are largely independent of any currency profits. Notably, of all the countries studied, as reported by Chui, Titman and Wei (2000), Japan is the only developed stock exchange that does not exhibit the momentum effect.

## 2.2 Australian Evidence

Hurn and Pavlov (2003) investigated momentum in Australian stock returns using monthly data on the top 200 stocks by market capitalization, covering 1973-1998. They find the existence of short to medium term momentum in Australian stocks. Using daily data, Demir et al (2004) investigated momentum for stocks that are Approved Securities on the ASX, from 1990-2001 and all stocks that are included in the All Ordinaries Index, from 1996-2001. They find that momentum returns are of greater magnitude than previously found in other markets. Durand et al (2006) examine stocks listed on the ASX from 1980-2001, using monthly data and do not find any evidence of a momentum effect. They instead find a strong seasonal effect associated with July, the first month of the Australian financial year. Acknowledging the clear discrepancy between their overall

[2] Austria, Belgium, Denmark, France, Germany, Italy, the Netherlands, Norway, Spain, Sweden, Switzerland and the UK, over the period 1980-1995.

[3] Hong Kong, Malaysia, Singapore, South Korea, Taiwan and Thailand, over the period 1979-1994.

conclusion and the strong finding of Demir et al that there is such an effect, they attempt to reconcile the results. Using daily returns, similar stocks and the same sample period as Demir et al they are able to broadly duplicate the results of Demir et al. However, this approach still fails to show any momentum effect over their original sample period, 1980-2001.

## 2.3 Source(s) of Momentum profits

Jegadeesh and Titman (1993) decomposed the momentum strategies' potential source of profits into three categories: (a) cross-sectional dispersion in expected returns where stocks with a high past return are expected to have high returns in the following period due to some risk characteristics; (b) serial correlation of the risk factor to which the portfolio returns are sensitive; (c) serial covariance of the firm specific components of security returns. They concluded that the momentum returns are driven by firm specific components, indicating that markets are not efficient.

Conrad and Kaul (1998) suggest that cross sectional variation in mean returns can explain profits to momentum strategies in NYSE/AMEX stocks (1948-1989). They argue that the momentum strategy involves buying high risk stocks and selling low risk stocks. Using the realized return of each stock as a measure of a stock's expected return, they avoid the need to specify an asset pricing model. However, the general evidence does not support this risk based explanation.

Moskowitz and Grinblatt (1999) find a strong momentum effect across industries. A strategy that involves buying (selling) stocks in an industry that performed well (poorly) over a past period will generate abnormal returns similar to that reported by Jegadeesh and Titman (1993). The abnormal returns persist even after adjusting for microstructure differences. They examined the profitability of a "random industry" strategy and it generates zero abnormal profits. Thus they concluded that the momentum returns are in fact driven by industry momentum and not firm specific components. Grundy and Martin (2001) re-examined the extent of momentum profits that were driven by industry momentum. They found that the zero return of the "random industry" portfolio is mainly due to negative serial correlation of returns in the first week after portfolio formation. When the "random industry" portfolio is formed after skipping one month from the ranking period, the momentum strategy earns significant profit of 0.79% per month.

## 2.4 Behavioral Models

Behavioral models propose that momentum returns are the result of trading by investors with psychological biases, that moves stock prices away from their equilibrium value. Within this framework, the number of irrational agents and the intensity of their trading will affect the degree of momentum exhibited.

Barberis, Shleifer and Vishny (1998) showed that “conservatism bias” might lead investors to under-react to information. If investors underweight new information when updating their beliefs, prices will slowly adjust to new information and thus cause return momentum. In addition, the authors posit that investors suffer from a “representative heuristic”. Investors consistently attempt to identify patterns from a series of returns that are random. This leads to investors placing too high a probability on the event that firms realizing extraordinary earnings growth will continue to do so. In combination, these two investor behaviors will lead to the observation of under reaction to initial good news and then overshooting the fundamental value when investors trade based on representative heuristics.

Daniel, Hirshleifer and Subramanyam (1998) suggest other forms of investor irrationality that may cause momentum returns. The authors argue that informed investors suffer from the psychological biases of “self-attribution” and “over-confidence”. In this model investors attribute the good performance of their stock picks to their own skills, while blaming bad luck on the stocks that performed badly. This behavior results in overconfidence and investors will overestimate the precision of their interpretation of new information. Thus on average, news generates momentum in the medium term but the weight of public information eventually produces long-term reversals.

Hong and Stein (1999) consider the presence of two groups of investors, the “news watchers” and the “trend followers”. This model requires the news watchers to trade on all information other than past price performance and the trend followers to trade based on past price performance and overlook fundamentals. Thus new information is only partially incorporated into the market giving rise initially to under-reaction. Subsequently, trend watchers extrapolate past price movements pushing prices above fundamental value.  In the long run prices revert to fundamental value.

Grinblatt and Han (2005) propose a model where prices deviate from fundamental value due to a behavioral phenomenon known as “the disposition effect”. This is the tendency of investors to hold on to their losing stocks while selling the winning stocks too early.[4] The authors argue that the effect causes a shift in the aggregate demand of a stock such that it will be higher (lower) after a price drop (increase). Assuming that the demand function for stocks is not perfectly elastic, the shift in demand will induce under-reaction to public information which ultimately leads to a momentum effect.

[4] Odean (1998) studied the accounts of investors in a large discount brokerage and found that there is a tendency to sell stocks with paper gains rather than stocks with paper losses.

## 2.5 Market States and Behavioral Models

General investor sentiment is perhaps best captured by the underlying performance of the market. Cooper, Gutierrez, Hameed (2004) hypothesized that if momentum profits were indeed driven by investor irrationality as described by the behavioural models, the profits from these strategies will vary with the state of the market. Furthermore, the pattern of the observed profits can be used to distinguish between the different behavioural theories that seek to explain momentum. In particular, they consider the theories of Daniel, Hirshleifer and Subramanyam (1998) and Hong and Stein (1999).

In the model of Daniel, Hirshleifer and Subramanyam (1998) it would seem likely that, on average, an increasing market will fuel the investing public's confidence. Acting on this increased confidence in their private information; investors would presumably drive prices further away from fundamentals and thus cause a higher degree of intermediate price continuation. In Hong and Stein's (1999) model, decreasing the levels of risk aversion of momentum traders will accelerate the price reaction to new information. At the same time, more momentum trading will also result in greater over-reaction to the news and greater momentum. Subsequently, there will be greater price reversal in the long run. Thaler and Johnson (1990) suggest that prior losses or gains experienced by investors influence their subsequent risk aversion when they make similar decisions. Barberis, Huang and Santos (2001) find that this 'house money' effect causes investors to have lower risk aversion after rising markets. We might therefore expect greater intermediate term momentum but also greater reversals in the long run after rising markets.

Cooper, Gutierrez, Hameed (2004) found that momentum profits exclusively follow market gains and these returns are reversed in the long run. These empirical findings are broadly consistent with the predictions of the models of both Daniel, Hirshleifer and Subramanyam (1998) and Hong and Stein (1999).

In the Grinblatt and Han (2005) model, the critical variable that predicts the level of under-reaction is the reference price used by investors in their mental accounts. Grinblatt and Han called the difference in reference price and current market price the *capital overhang*. They argue that the cost price is likely to be the reference price in the investor's mental accounts. However, the authors did concede that investors could possibly use other forms of benchmarks when forming mental accounts. It seems reasonable that market conditions can influence the reference price by which an investor evaluates the capital gains/loss of each stock. If investors care more about gains/losses relative to the performance of a market benchmark than absolute gains/losses relative to the purchase price, the market returns could be a better proxy for the *capital overhang* which ultimately predicts the degree of under-reaction to subsequent news.

Extending the Grinblatt and Han (2005) model, such that investors incorporate contemporaneous market conditions into their valuation of investments, yields predictions of asymmetric stock reaction conditioned on the past returns of both individual firms and the market. Following a decreasing market, investors view past winners as having relatively higher capital gains in their mental accounts. The performance of the winner 'seems' to be far better than the rest of the market, making the investors more risk averse. This increases the tendency for investors to 'cash-in' on their winners too early.[5] The high level of *capital gain overhang* following a down market implies that winners will exhibit more momentum following down markets. Conversely, after an increasing market, the investor will view winners as having performed 'on par' with the rest of the market. This reduces the tendency to realize the gains immediately.

For losers, the opposite effects are predicted following market movements. Following a decreasing market, the losses from the losers tend to be less painful since the rest of the market has experienced losses as well. Therefore, investors do not become especially risk loving. Subsequently, they will not be so reluctant to realize capital losses. Conversely, after a rising market, the loss suffered by the losers seems to be magnified compared to the rest of the market. As such, the large amount of capital loss may induce the investor to be risk seeking. Ultimately, the investors will tend to hold the losers longer.

The Grinblatt and Han (2005) model of under-reaction therefore predicts that winners (losers) will experience weaker (stronger) momentum following "UP" market states. Conversely, the model predicts that winners (losers) will experience stronger (weaker) momentum following "DOWN" market states.

Therefore, market states can be used to evaluate the predictions of competing behavioural explanations. The over-reaction models of Daniel et al (1998) and Hong and Stein (1999) predict greater momentum and subsequent long run reversal after rising markets. However, the Grinblatt and Han (2005) under-reaction model predicts that market states have an asymmetric effect on winners and losers. After a rising (decreasing) market, the losers (winners) will exhibit greater momentum. Furthermore since Grinblatt and Han's model is motivated by disposition based trading that prevents fundamental news from being imputed into prices, their model does not predict long run reversals.

[5] Under prospect theory, investors become more risk averse in the domain of gains. Since investors deem winners that follow an up market as having made extraordinary gains within their mental accounts, they become more risk averse and more anxious to realise their capital gains.

## 3. Data and Methodology

Our sample comprises daily data of stocks listed on the ASX during the period January 1991 to September 2002. A total of 2199 different shares were included in the sample obtained from the SIRCA daily data database. The All Ordinaries index, used to proxy the market, is provided by ASX and SIRCA.

The reported momentum profits will have more economic meaning if the required trading involved in the momentum strategy, while hypothetical, is practical. Thus, our use of daily data. The advantage of using daily data is the elimination of the potential for a look ahead bias of most momentum studies. For example, when the last trade of a particular stock did not occur at the month end, it is assumed that this fact is known before the month end. In a practical sense, the correct ex-post price to be used is the next traded price in the next month. This problem will be most pronounced in samples with illiquid stocks that trade infrequently, as is common in the Australian market.

The momentum strategy involves constructing 10 portfolios of stocks based on past price performance. Following previous work (e.g. Jegadeesh and Titman 2001) the stocks are sorted by their prior 6-month returns and each portfolio is then held for K-months (where K is 1, 3, 6, 9 and 12).[6] Accordingly, we refer to the '6xK' momentum strategy. Since this study uses daily data, time windows nominally measured in calendar months are calculated in exact numbers of days to ease computation.[7] Furthermore, the prices of the stocks are evaluated on each Wednesday since using the mid-week reference point for the share's price avoids the well-known day-of-the-week effect. In addition, a one-week lag is ensured between the formation and holding periods to circumvent the problems of bid-ask bounce, price pressure and lagged reaction effects reported in Jegadeesh (1990) and Lehmann (1990).

A trading model is developed which removes look-ahead bias and also acts as a natural filter against illiquid stocks. For example, when evaluating a 6x1 momentum strategy, the pre-formation 6-month return of each stock at time t, based on the price of the stock at day t and day t-182, is required. If there wasn't a trade on day t-182, the next actual traded price is used. If there isn't a traded price on day t, then the traded price on the previous day is used. This eliminates look-ahead bias because the subsequent ranking process will only use price information available at time t.

In calculating the 1-month holding return of each portfolio, the stock price on day t+7 and t+35 will be required. If there was no actual trading on day t+7, the momentum trader will have to delay

[6] As a robustness check, portfolios were also selected based on other periods of J-month past returns (where J is 1, 3, 6, 9, 12). The findings were robust to different selection periods so results for periods other than six months have not been presented to conserve space.

[7] Specifically, 3 months = 13 weeks, 6 months = 26 weeks, 9 months = 39 and 12 months = 52 weeks.

action until the next available trade.[8] At the time of closing out the momentum strategy on day t +35, the actual investor's achievable price is on the next trade. For tractability it is assumed that a stock is filtered from the universe of stocks when there is no trade within 5 days of time t-182, t or t+7. This filter rule will eliminate the most illiquid stocks and will tend to bias the results against finding significant momentum returns.

The trading model described above highlights the difficulty in forming a zero-cost momentum portfolio. A zero-cost portfolio is formed when the dollar amount spent on the winner portfolio is the same as the dollar amount derived from *simultaneously* selling the losers. This is a near impossibility when the stocks are not traded at the same time and the momentum investor does not know ex-ante the price of each trade. The calculation of value weighed returns is similarly affected although it can be circumvented by calculating the weight of each stock based on the market value at time t instead of t+7.

The zero cost momentum strategy involves buying (selling) stocks that have the best (worst) past price performance. Both equal and value weighted portfolio returns are considered. Overlapping portfolios are formed at the end of each month. The return of the strategy is calculated as the average return of the stocks in the winner portfolio less the average return of the stocks in the loser portfolio. Buy-and-hold returns (BHAR) and monthly compounded returns are reported. The BHAR is reported because it represents the actual return achieved by the momentum strategy and the average monthly compounded return is reported to be consistent with the existing literature and allow comparability of momentum strategies with different holding periods.

## 4. Empirical Results

4.1 Momentum Returns.

Table 1 reports the returns for the 6-K momentum strategies. The one-month momentum returns are insignificant, but then monotonically increase and peak at the 6$^{th}$ month where the strategy seems to experience reversals in the long run. The average monthly return for the strategy with a 6 month holding period is 0.62% per month and significant, which is of similar magnitude to prior studies. The long run reversal effect is pronounced with a reversal of about 0.97% per month for a 24 month holding period.[9]

Interestingly, the return continuation behaviour seems to be limited to stocks in the winner decile while the losers tend to exhibit contrarian behaviour in both the short and long term. For example, the return from buying winners for a 6-6 strategy is 2.27% per month. However, the return for shorting the counterpart loser decile is -1.65%. This asymmetry contrasts with prior

[8] Alternatively, it can be assumed that the investor will trade at the bid price for a sale and ask price for a purchase.

[9] Test statistics for the momentum portfolio returns are HAC-consistent (Newey-West, 1987).

studies. For US data, Hong, Lim and Stein (2000) report that 73%-100% of the momentum returns is determined by the 'loser' portfolio. Demir et al (2004), who used Australian data, found that close to 76% of their reported profits are sourced from the losers. Since the authors limit their samples to stocks in the 'approved list', it appears that the reversals documented here are driven by the stocks outside of the approved list.

Some researchers have argued that the reported profits from momentum are not attainable because the profits are mainly contributed from short-selling the losers. The results documented in Table 1 suggest that, for our dataset, the return continuation of stocks can potentially be exploited by utilizing one leg of the momentum strategy alone, going long on past winners. The corresponding leg of shorting losers on average had negative returns over the sample period. This modified strategy potentially circumvents the cost or restrictions on shorting stocks. However, a strategy that goes long on winners alone is substantially different from the momentum strategies of the literature since it cannot be executed as a zero-cost or risk neutral portfolio.

## 4.2 Robustness Tests

### 4.2.1 Equal vs. Value weighted and Excess vs. Abnormal returns

Since all of the stocks in the SIRCA database are used in this study, there is a concern that the results obtained using equal weighted returns may be biased towards small and illiquid stocks. To the extent that these small capitalization stocks cost more to trade, the reported profits may not have economic relevance because they are not directly achievable after accounting for market frictions. To control for the influence of small stocks in the reported returns, we examined value weighted average portfolio returns that attach more weight to stocks with relatively larger market capitalizations.

Table 2 reports the momentum strategy returns for 6-K strategies when the winner and loser deciles are both equal weighted and value weighted and calculated using excess returns and abnormal returns. The momentum deciles are constructed using the same methodology described above. However, there are some variations in the calculations of the holding period returns of the winner and loser deciles. The average return of the portfolio is either the simple average of all stocks in the portfolio or it is value weighted. The returns are also calculated as returns above the risk free rate (excess return) or returns above the expected return from the CAPM (abnormal return). At every ranking period, we run individual CAPM regressions on each stock using data from the prior 200 trading days.

The value weighted metrics for calculating average momentum strategy returns seems to yield higher returns than the equal weighted approach. For the 6-6 strategy, the average monthly value weighted momentum excess return is 2.81% compared to the equal weighted excess return of

0.62% (the corresponding abnormal returns are 2.72% and 1.17%). This prima facie evidence that the momentum effect in Australia is concentrated amongst the larger stocks is difficult to reconcile with the findings of other researchers who find that momentum is largely a small firm effect in the US.

The better performance of the value weighted scheme is mainly driven by the loser decile. In fact, while the losers in the equal weighted scheme all experience reversals, the losers in the value weighted scheme exhibit return continuation of about the same magnitude as the winner decile. For example, in the 6-6 strategy, shorting the equal weighted loser decile yields a return of -1.7% per month while shorting the value weighted decile yields a return of 1.57% (a spread of 3.27%). On the other hand, for winners, the equal weighted portfolio performs better than the value weighted portfolio (2.27% and 1.45%). It appears that small losers tend to experience reversal while large losers experience continuation and small winners exhibit more return continuation than large winners. As such, the most efficient strategy in terms of absolute returns may in fact be shorting large losers and buying small winners.[10]

The CAPM risk adjustment increases the reported returns for equal weighted strategies. Since the expected returns of the winners are relatively lower than the losers, the abnormal returns for the winners will be relatively higher for the same level of excess returns. For the 6-6 strategy, the abnormal equal weighted return of the strategy is 1.17% compared to 0.62% for the reported excess return. Thus, correcting for exposure to beta risk actually increases the returns of the momentum strategy instead of reducing it. This evidence is consistent with evidence reported elsewhere that momentum profits cannot be explained by cross sectional differences in exposure to beta risk.

The risk adjustment for the value weighted portfolios have less impact on the reported results. The spread between the excess value weighted return and the abnormal value weighted return is on average about 0.09% (the same spread is -0.55% for equal weighted returns). This suggests that for larger stocks, there is little difference in beta risk between winners and losers.

### 4.2.2 Trading algorithm and skipping 1 week between ranking and holding period

The institutional setting of the Australian market is such that there is a strong concern that outside of the 200 largest firms, a large proportion of firms are illiquid and suffer from asynchronous trading. Returns calculated on illiquid stocks using historical prices potentially lack economic relevance for two reasons. First, recorded prices on the dataset do not necessarily reflect the price that is required to clear the market. If an illiquid stock does not trade for an extended period of

[10] Shorting large losers and buying small winners may expose the trader to the SMB risk factor of Fama and French (1993), as well as increasing exposure to illiquidity risk.

time, SIRCA (and most other data sources) report the price of a stock as the last traded price (regardless of how long ago the last trade was made). Second, the trading on an illiquid stock may move the price of the stock significantly away from the price recorded on the dataset.

There are two approaches to control for the liquidity issue documented in the literature. First, researchers typically filter out stocks that are deemed to be illiquid. Jegadeesh and Titman (1993, 2001) filter stocks that are priced below US$5.00. In Australia, Demir et al (2004) only examined stocks that are in the All Ordinaries index. In combination with the low price filter, Jegadeesh and Titman (1993) skipped a month between the ranking and formation period to circumvent potential microstructure effects, such as bid ask bounce in illiquid stocks. In a novel approach, our study computes the holding period return using a trading algorithm that adjusts for illiquid trading. The algorithm replaces the last traded price recorded in a historical dataset with the next available price when calculating returns of infrequently traded firms. We argue that this process gives a more accurate description for the actual return for a momentum trading strategy.

#### 4.2.3 Consistency with other Australian Evidence

As discussed earlier, Demir et al (2004) also examined the momentum effect in the Australian market. While there are critical differences in the research focus and the research design between their study and ours, this section will reconcile the results presented in their paper with those reported here. Demir et al (2004) analysed momentum strategies over the sample period September 1990 to July 2001 using the SIRCA database, hence, their sample significantly overlaps the sample period of this study. The authors reported significant momentum profits of up to 5.34% per month (Demir et al, 2004, Table 2, 180-30 day strategy).

The major differences in the methodology of Demir et al (2004) and this paper are (a) we examine a more comprehensive sample of stocks; (b) Demir et al reported returns for non-overlapping portfolios; (c) Demir et al used contiguous ranking and holding periods while we control for illiquidity by skipping 1 week between ranking and holding period and computing returns using a trading algorithm; and (d) we define the ranking and holding periods on the basis of trading days rather than calendar months.

Demir et al (2004) use a ranking period of 30, 60, 90 and 180 trading days which translates into 6, 12, 18 and 36 weeks. In this study, ranking periods of 4, 13, 26, 39 and 52 weeks are used instead. To keep the analysis tractable, when replicating the research design of Demir et al (2004), we replace their ranking periods with the ones used in this paper. Thus, for this section, we will focus on a comparison of the impact of extending the sample of stocks from the large capitalization stocks in the Approved List to the entire universe of stocks in the SIRCA database.

Table 3 reconciles the results in this paper with those reported by Demir et al (2004). Panel A replicates the research design of Demir et al (2004). Specifically, we limit the data universe to the Approved list, we do not skip 1 week between formation and holding period and finally, we only exclude stocks that do not trade during the formation period. In Panel B, we only partially replicate Demir et al (2004) by using a sample from stocks in the ASX Approved List while reverting to the research design used in this study.[11] Finally in Panel C, we reproduce the results of this study using a research design that uses the entire sample.

The momentum strategy returns calculated using the Demir et al (2004) methodology, reported in Panel A Table 3, are consistent with those reported in Demir (2004). For example, for a short ranking period strategy (1 month here, but 30 trading days in Demir), the holding period return peaks after 3 months (or 60 trading days). The magnitude of the return for the 1 month strategies reported here are lower than the 30 day strategies reported in Demir et al because the 30 day strategy uses a longer ranking horizon. The 6 month ranking strategies reported here closely mimic Demir et al: eg the 6-3 months momentum strategy's average monthly return is 3.80% (test stat = 14.9), while Demir reports a 90-60 days strategy return of 3.08% (test stat =8.91).

Comparing the momentum strategy returns of Panels A and B, the differences in the methodology adopted by this study and Demir et al does not appear to significantly change the reported returns nor is it expected to do so. The innovations in this papers' methodology are designed to control for stale prices of illiquid firms while the sample used in both Panels A and B is limited to the stocks on the Approved list which are, by definition, the most liquid stocks on the ASX. The results in Panels A and B confirm that the reported returns of Demir et al (2004) are robust to the look-ahead bias because their sample is limited to large liquid stocks only.

The main focus of this section is to examine if extending the sample of the stocks from the Approved list to a wider base of stocks can potentially impact the profitability of the momentum strategies. However, the implementation of momentum strategies that include stocks outside of the ASX approved list poses two practical problems. First, short-selling is not permitted for these stocks and second, these stocks may be illiquid and the measurement of their returns may be biased. The short-selling problem is discussed in sub-section 4.1 and the bias in measuring the returns of illiquid firms is addressed by the trading algorithm designed to replace stale prices with the next traded price. Comparing Panels B and C, the momentum strategy returns are higher when the sample is limited to the stocks in the 'Approved list'. The improvements in the strategy returns are a combination of lower reversals of losers in the approved list and greater continuation in the winners.

[11] Specifically, (a) we use firms in the approved list alone, but (b) skip a week between formation and holding period and (c) filter out stocks that do not trade within 5 days of the start of the holding period.

Thus, the evidence presented here, in combination with Demir et al (2004), indicates that in Australia at least, the momentum effect is more pronounced in stocks in the ‘Approved list’ which are generally larger and more liquid than the rest of the sample. However, extending the strategy to a larger sample of stocks remains significantly profitable.

### 4.3 Seasonality

#### 4.3.1 Monthly Effects

Next, we consider whether the type of seasonal effects documented in the US can be observed in the Australian market. Table 4 reports the returns that momentum strategies yield over each calendar month. For example, the average 6-6 momentum strategy monthly return for the month of January is the average return during January of momentum strategies that begin in July, through to December the year before. For tractability, the table reports the average monthly return for 6-K month momentum strategies over the months most relevant to our discussion.

As expected, the reversals of the losers seem to be quite pronounced during the month immediately after the Australian and US financial year end. For example, in the 6-6 strategy, the returns from shorting a portfolio of losers will yield -10.88% and -6.55% in January and July, respectively, causing the momentum strategy to yield losses of -3.49% and -3.31%. This evidence is consistent with that of Brown et al (1983) who documented reversal of losers in the months of January and July for a sample of Australian stocks over the period from 1958 to 1979. If we remove the negative impact of strong reversals in January and July, the average return for the losers is -1.19% per month. The momentum strategy’s profit then becomes a positive 0.48% per month. Effects associated with the end of the financial year are associated with the tax loss selling hypotheses of Keim (1983). However, there are some problems with these hypotheses. For example, the reversals in the month of January are larger in magnitude than those in July. This seems hard to entirely reconcile with the a tax loss selling explanation since it is unlikely that the Australian and US markets are so integrated that investors influenced by the US tax laws have a greater impact than local investors under the Australian tax regime. It is plausible that the reversals of losers in the month of January and July are more driven by other factors that create high buying pressure in these months (see Brown et al (1983) for a detailed discussion of these issues with regard to the Australian market).

The tax loss selling hypothesis relies on the fact that investors hold off realising their tax losses until the end of the financial year. The normal reluctance to crystallize losses, known as the ‘disposition effect’ is overcome in the month of June (December for US) by the potential benefit in claiming tax losses for the financial year.

The tax year end is not the only possible event that may trigger a reduction in the disposition effect and influence investors to sell losers. If investors (whether individual or institutional) create 'mental accounts' of their investments in a way that leads them to review the portfolio performance at specific periods, such as the end of December or June, it is then plausible that the end of these calendar months become strong anchoring points in which they rebalance their portfolios.

Institutional investors may also engage in 'window-dressing' (see Sias, 2007). Since fund managers typically report their performance and asset holdings quarterly, there is a motivation to sell off assets that have performed poorly in the past so that they do not have to report the identity of their misjudged investments in the balance sheet of their quarterly reports. This again creates a high selling pressure in the month preceding the end of each quarter and higher buying pressure in the first month of each quarter.

Figure 1 is a histogram of the average monthly returns from the 6-6 momentum strategy, which includes buying the winner decile or shorting the loser decile for each calendar month. Losers, on average, experience reversal over a 6 month holding period. Stocks in the loser decile only exhibit return continuation in the months of March and June. On the other hand, the reversals of losers clearly occur in the months of January, April and July. However, quarterly effects expected in the month of October are instead borne out in the month of November. In all four instances, the reversal of losers is stronger for the start of one quarter compared to the end of the previous quarter, which is consistent with the predictions of the window-dressing hypothesis. For example, the spread in the difference of the return in June and July for the loser decile is 10.54% (3.99% + 6.55%).

4.4 Subperiod Results

To further examine the momentum effect in Australia, Table 5 reports the average monthly return of momentum strategies that were started in different calendar years. For example, the 1 month holding period return of 1.37% per month in the year 1994 is the average of all 6-1 momentum strategies that were initiated in 1994. These average monthly returns can be interpreted as the profit available for an investor that implemented the momentum strategy from the start to the end of a particular year.

The results presented here clearly illustrate that the momentum strategies, which on average are profitable over the full period of 1991-2002, have substantial risk. The momentum trader may be faced with a large loss when measuring returns on a yearly basis. For example, for a 6-6 strategy, which on average yields 0.62% per month over the 11 year period, actually makes a loss of -2.62% per month (36% pa) in the year of 1993. The best performing year for this strategy is in 2001 where the return is 2.41% per month. Indeed, over all holding periods, the average return is highly variable. The spread from the best performing year to the worst year is about 6.9% per month on average for the 7 holding periods. When the sample is divided into two sub-samples, the returns over the second half of the period are generally higher than the first half of the sample. For a 6-6 strategy, for example, the monthly return over 1991-1996 is -0.05% and insignificant but the return is 1.31% and significant when measured over 1996-2002.

The sensitivity of the momentum returns to the particular sample period is important for at least two reasons. First, the results presented here highlight that the momentum strategy is in fact risky (as measured in terms of variations in annual returns as opposed to loadings on market risk).[12] Second, it seems counter-intuitive that momentum returns are more profitable in the later half of the sample since we would expect that market participants 'learn' from the widespread evidence that has been documented in the empirical literature. Schwert (2002) examined a wide range of documented anomalous effects in the literature and found that a majority of these effects diminish after some time has lapsed from the first documentation of these effects. Consistent with the evidence presented here, he also failed to find evidence that market participants have learned to exploit the momentum effect.

The inability of market participants to fully exploit momentum in Australia could possibly be due to two factors. First, the underlying mechanism that drives the momentum effect has become more prevalent or second, the market frictions that prohibit investors from engaging in momentum strategies has increased. Of the two possible explanations, it is hard to find any compelling evidence that market frictions have increased over the two sub-periods. While little is yet known about the exact source of the momentum returns, the main systematic difference between the environments in the two sub-periods would seem to be the bull-run in the world economy over the late 1990s and early 2000s. In sub section 4.5, we examine if the yearly effect observed here can be explained by underlying market conditions.

### 4.5 Market States

In this sub-section, we examine the role of market state as a conditioning variable to examine behavioural explanations for momentum strategies. In particular we seek to find empirical data to distinguish between the alternative behavioural models that have been proposed as explanations of the momentum effect. To proxy for the underlying condition of the market, the market returns over the past 6 months is calculated at the start of each holding period and then used to classify the market into three states, UP, NEUTRAL and DOWN.

[12] In unreported results, when the stock returns are adjusted for their beta risk, the pattern in momentum profits across years remains robust.

Table 6 reports the value-weighted 6-K momentum strategy returns following different market states. Panel A reports the returns when UP and DOWN market states are defined as one standard deviation above or below the time series mean. Panel B reports the results when the market states are defined as above or below an annualized excess return of 10%.[13]

From Panel A of Table 6, the momentum strategies following UP markets initially seem to perform better than after DOWN markets. For example, the return (Mth ret) of the 6-6 strategy following UP markets is 1.17% compared to 0.69% following DOWN markets. In the long run, the momentum strategy returns seem to suffer from reversals. The reversal is also more severe for strategies following UP market states as predicted by the over-reaction models of Daniel, Hirshleifer and Subramanyam (1998) and Hong and Stein (1999). The return for the momentum strategy following UP market states is -3.91% (-0.17% per month) over 24 months compared to 13.9% (0.54% per month) following DOWN market states.

The observation that following UP markets, momentum is stronger in the intermediate term which then leads to greater reversal in the long term is consistent with the predictions of Daniel, Hirshleifer and Subramanyam (1998) and Hong and Stein (1999). As discussed in sub-section 2.5, the Daniel, Hirshleifer and Subramanyam (1998) model predicts that investors become more confident about their private signals following an increasing market which subsequently causes greater over-reaction to news. Similarly, in the Hong and Stein (1999) model, investors become more risk tolerant following increasing markets and over-react to news. The performance of momentum returns conditioned by market states is consistent with the results reported by Cooper et al (2004).

However, there are some striking empirical observations that cannot be explained by the over-reaction models. There is a strong asymmetric reaction for winners and losers when conditioning on market states. Specifically, winners perform better following DOWN states while losers exhibit more momentum following UP states. The over-reaction models cannot explain this asymmetric behaviour of winner and losers when conditioned by market states. For example, the Daniel, Hirshleifer and Subramanyam (1998) model predicts that investors will be more overconfident about their private information following UP market states which will lead them to over-react to good news and will ultimately cause greater momentum for winners. However, the performance of winners following UP market states is much lower than after DOWN states. Conversely, the momentum behaviour of losers is stronger following UP states than following DOWN states.

These results are consistent with the Grinblatt and Han (2005) disposition model. Their model proposes that investors use market returns as benchmarks in their investing decisions. After rising

[13] The cut off points are arbitrary but the classification is a sufficient measure of investor sentiment during the period. Alternatively, Cooper, Gutierrez and Hameed (2004) defined up (down) markets as one that had a positive (negative) 3 year return.

markets, investors hold on to their losers longer as they seek to avoid the pain of realizing capital losses. Conversely, after decreasing markets, investors become more risk averse and prematurely sell their winners to realize the capital gains. Thus, the model predicts an asymmetric response of winners and loser to market states where winners experience greater momentum after decreasing markets and vice-versa for losers.

In conclusion, while the returns of the winner – loser momentum strategy is consistent with the over-reaction models, we show that the separate behaviour of winners and losers is instead consistent with the Grinblatt and Han (2005) model.[14]

**5. Conclusion**

The finance literature is now replete with much evidence of a momentum effect. Jegadeesh and Titman (1993, 1995) and others since, report significant positive returns by buying 'winners' and selling 'losers'. The current paper contributes to the momentum literature by presenting out of sample information on the effect in the Australian market over the period 1991 to 2002.

Based on a methodology that avoids the look-ahead bias of many momentum studies that employ monthly data, we confirm the existence of a momentum effect in Australia. In contrast to previous studies, the effect is stronger amongst larger companies. Interestingly, the greater proportion of the profits of the momentum strategy has been contributed by the long side of the trading strategy making profits attainable even in the presence of short-sale constraints. We also find strong seasonal influences which are consistent with the tax selling hypothesis and institutional 'window dressing'. We also show that momentum returns are highly variable over time – strategies employed in the late 1990s generate higher returns than those in the early 1990s.

The variability of the momentum return strategy reported herein suggests that the momentum investor faces risks that have not been examined in the literature. For example, although the '6x6' strategy on average earns positive returns, it is only profitable less than 2/3 of the time. Potentially the investor may be faced with liquidation costs in loss-making situations. The fact that it is impossible for a zero-cost strategy to be implemented ex-ante is another source of risk to the trader.

Finally, the current set of results suggests that some aspects of the effect are quite different from those previously observed in the US and other international markets. This is theoretically encouraging because future research can use Australian data to test the out of sample power of models developed to explain empirical findings in the US. In this paper, we use information on the inter-temporal performance of 'winners' and 'losers' in different market states to determine which of a number of behavioral theories are most predictive of the observed movements of the Australian

[14] Cooper et al (2004) who find that their results are consistent with over-reaction models do not examine the performance of winners and losers separately.

market. The evidence indicates that models based on the disposition effect better fit the observed data than models based on the presumption of an overreaction bias.

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## Table 1: Momentum Returns – Overall Results

This table displays momentum returns for trading strategies with 6 months formation periods and 1, 3, 6, 9, 12, 18 and 24 holding periods. Stocks are allocated into 10 deciles based on their past performance each Wednesday. The momentum strategy involves going long (short) on the stocks in the winner (loser) portfolio. Extremely low priced stocks (below $0.50) and illiquid (no trades within 5 days of the end of ranking period) stocks are excluded from the analysis. These trades are implemented 1 week after the ranking date. If a stock is de-listed before the end of the holding period, it is assumed that the stock is sold at the last traded price and the proceeds are invested at the risk free rate. The return of the momentum strategy is computed as the average return of the winners minus the losers. The buy and hold return (BHAR) and the average monthly returns are reported. Equal weighted average excess returns (%) for the momentum trading strategies for the sample period of January 1991 to September 2002. The student t-statistic adjusted for HAC errors are shown ('T Stat'). The return from going long on the winner portfolio ('Winner') and shorting the loser portfolio ('Loser') is shown separately.

| | K: Holding Period | | | | | | |
|---|---|---|---|---|---|---|---|
| | 1 | 3 | 6 | 9 | 12 | 18 | 24 |
| BHAR | -0.18% | 1.93% | 3.79% | 1.38% | -3.76% | -13.43% | -20.82% |
| **Mth Ret** | **-0.18%** | **0.64%** | **0.62%** | **0.15%** | **-0.32%** | **-0.80%** | **-0.97%** |
| T Stat | 0.19 | 2.03 | 2.35 | 0.99 | -0.55 | -2.50 | -3.62 |
| Winner | 2.37% | 2.44% | 2.27% | 1.97% | 1.70% | 1.35% | 1.07% |
| Loser | -2.55% | -1.80% | -1.65% | -1.82% | -2.02% | -2.14% | -2.04% |
| No | 552 | 552 | 552 | 540 | 527 | 502 | 476 |

**Table 2: Momentum Returns - Equal vs. Value and Excess vs. Abnormal weighted returns**

This table displays momentum returns for trading strategies with a 6 month formation period and 1, 3, 6, 9, 12, 18 and 24 holding periods. Stocks are allocated into 10 deciles based on their past performance each Wednesday. The momentum strategy involves going long (short) in the stocks in the winner (loser) portfolio. Extremely low priced stocks (below $0.50) and illiquid (no trades within 5 days of the end of ranking period) stocks are excluded from the analysis. These trades are implemented 1 week after the ranking date. If a stock is de-listed before the end of the holding period, it is assumed that the stock is sold at the last traded price and the proceeds are invested at the risk free rate. The return of the momentum strategy is computed as the average return of the winners minus the losers. The buy and hold return (BHAR) and the average monthly returns are reported. Panel A reports returns (%) for the momentum trading strategies, based on excess returns, for the sample period of January 1991 to September 2002. Panel B reports returns, based on CAPM risk-adjustment, for the period January 1995 to September 2002. The CAPM beta of each stock is estimated using 200 daily returns prior to the formation date. The student t-statistic values are shown ('T Stat'). The return from going long on the winner portfolio ('Winner') and shorting the loser portfolio ('Loser') is shown separately.

| | | K: Holding Months | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Weight | | 1 | 3 | 6 | 9 | 12 | 18 | 24 |
| Panel A: Excess Return | | | | | | | | |
| Equal | BHAR | -0.18% | 1.93% | 3.79% | 1.38% | -3.76% | -13.43% | -20.82% |
| | **Mth ret** | **-0.18%** | **0.64%** | **0.62%** | **0.15%** | **-0.32%** | **-0.80%** | **-0.97%** |
| | T Stat | -0.310 | 1.532 | 1.856 | 0.499 | -1.051 | -3.005 | -4.125 |
| | Winner | 2.37% | 2.44% | 2.27% | 1.97% | 1.70% | 1.35% | 1.07% |
| | Loser | -2.55% | -1.83% | -1.70% | -1.84% | -1.95% | -1.91% | -1.70% |
| Value | BHAR | 3.59% | 11.76% | 18.09% | 22.43% | 20.15% | 9.72% | -1.32% |
| | **Mth ret** | **3.59%** | **3.78%** | **2.81%** | **2.27%** | **1.54%** | **0.52%** | **-0.06%** |
| | T Stat | 5.234 | 10.106 | 12.019 | 12.641 | 10.095 | 4.028 | -0.515 |
| | Winner | 1.91% | 2.11% | 1.45% | 1.05% | 0.58% | -0.01% | -0.19% |
| | Loser | 1.67% | 1.80% | 1.57% | 1.48% | 1.15% | 0.57% | 0.14% |
| Panel B: Risk Adjusted Return | | | | | | | | |
| Equal | BHAR | 1.85% | 5.51% | 7.21% | 5.10% | 0.88% | -7.74% | -15.44% |
| | **Mth ret** | **1.85%** | **1.80%** | **1.17%** | **0.55%** | **0.07%** | **-0.45%** | **-0.70%** |
| | T Stat | 2.814 | 4.211 | 3.643 | 1.922 | 0.259 | -1.786 | -3.750 |
| | Winner | 3.88% | 3.86% | 2.83% | 2.44% | 2.38% | 1.71% | 0.93% |
| | Loser | -2.02% | -2.13% | -1.76% | -1.97% | -2.33% | -2.03% | -1.42% |
| Value | BHAR | 3.75% | 11.25% | 17.46% | 21.84% | 18.10% | 7.05% | -1.91% |
| | **Mth ret** | **3.75%** | **3.62%** | **2.72%** | **2.22%** | **1.40%** | **0.38%** | **-0.08%** |
| | T Stat | 5.009 | 8.920 | 11.034 | 12.131 | 8.851 | 2.990 | -0.757 |
| | Winner | 2.37% | 2.42% | 1.62% | 1.22% | 0.83% | 0.19% | -0.07% |
| | Loser | 1.38% | 1.28% | 1.26% | 1.20% | 0.66% | 0.20% | -0.01% |

## Table 3: Momentum Returns - Comparison to Demir et al (2004)

This table reconciles the results in this thesis against the results reported by Demir et al (2004). Demir et al (2004) studied momentum in Australia using the same SIRCA database over a period that significantly overlaps with this study. However, there are notable differences in their research design. 1) They limit firms in their analysis to those in the approved list, 2) they use contiguous returns between formation and holding periods and 3) they only filter out stocks that do not trade during the period. In Panel A, we replicate the research design of Demir et al (2004). Specifically, we limit the data sample to the Approved list, we do not skip 1 week between formation and holding period and finally, we only exclude stocks that do not trade during the formation period. In Panel B, we again replicate Demir et al (2004) using the Approved stocks only while reverting to the research design used in this study. Specifically we 1) limit the sample of firms to those in the approved list alone, but 2) skip a week between formation and holding period and 3) filter out stocks that do not trade within 5 days of the start of the holding period. Finally, in Panel C, we reproduce the results of this study using a research design that uses the entire sample, The buy and hold returns of the winner, loser and winner-loser portfolio of J-K strategies (where J= 6 and K= 1, 6, 12, 24) are reported. The test statistics for the momentum portfolio return is adjusted to be HAC-consistent (Newey and West, 1987). The student t-statistic values are shown ('T Stat'). The return from going long on the winner portfolio ('Winner') and shorting the loser portfolio ('Loser') is shown separately.

| | | K: Holding Months | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | 1 | 3 | 6 | 9 | 12 | 18 | 24 |
| Panel A: Approved and Demir et al (2004) | | | | | | | | |
| | BHAR | 3.95% | 11.83% | 19.73% | 26.81% | 29.38% | 26.25% | 23.26% |
| | **Mth Ret** | **3.95%** | **3.80%** | **3.05%** | **2.67%** | **2.17%** | **1.30%** | **0.88%** |
| | T Stat | 8.37 | 14.87 | 18.95 | 21.90 | 21.28 | 15.67 | 12.00 |
| | Winner | 1.76% | 1.80% | 1.62% | 1.48% | 1.24% | 0.83% | 0.62% |
| | Loser | 2.19% | 2.00% | 1.42% | 1.19% | 0.93% | 0.47% | 0.26% |
| Panel B: Approved only | | | | | | | | |
| | BHAR | 4.40% | 12.93% | 21.69% | 28.92% | 30.83% | 24.98% | 21.18% |
| | **Mth Ret** | **4.40%** | **4.14%** | **3.33%** | **2.86%** | **2.26%** | **1.25%** | **0.80%** |
| | T Stat | 8.33 | 14.36 | 18.67 | 21.23 | 19.47 | 12.16 | 8.66 |
| | Winner | 1.94% | 1.99% | 1.73% | 1.62% | 1.35% | 0.93% | 0.73% |
| | Loser | 2.45% | 2.15% | 1.59% | 1.24% | 0.91% | 0.31% | 0.08% |
| Panel C: Full Sample | | | | | | | | |
| | BHAR | -0.18% | 1.93% | 3.79% | 1.38% | -3.76% | -13.43% | -20.82% |
| | **Mth ret** | **-0.18%** | **0.64%** | **0.62%** | **0.15%** | **-0.32%** | **-0.80%** | **-0.97%** |
| | T Stat | -0.31 | 1.53 | 1.85 | 0.49 | -1.05 | -3.00 | -4.12 |
| | Winner | 2.37% | 2.44% | 2.27% | 1.97% | 1.70% | 1.35% | 1.07% |
| | Loser | -2.55% | -1.83% | -1.70% | -1.84% | -1.95% | -1.91% | -1.70% |

## Table 4: Momentum Returns across Different Months

This table displays momentum returns for trading strategies with a 6 month formation period and 1, 6, 12, 18 and 24 holding periods. Stocks are allocated into 10 deciles based on their past performance each Wednesday. The momentum strategy involves going long (short) on the stocks in the winner (loser) portfolio. Extremely low priced stocks (below $0.10) and illiquid (no trades within 5 days of the end of ranking period) stocks are excluded from the analysis. These trades are implemented 1 week after the ranking date. If a stock is de-listed before the end of the holding period, it is assumed that the stock is sold at the last traded price and the proceeds are invested at the risk free rate. The return of the momentum strategy is computed as the average return of the winners minus the losers. The student t-statistic values adjusted for HAC errors are shown ('T Stat'). The return from going long on the winner portfolio ('Winner') and shorting the loser portfolio ('Loser') is shown separately.

| | | Month | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| K: Holding Month | Data | March | Apr | Jun | Jul | Sep | Oct | Dec | Jan | Non Jan/July | Oct-Mar | Apr-Sep |
| 1 | **Mth Ret** | **2.77%** | **-4.59%** | **2.09%** | **-4.62%** | **-2.72%** | **-0.39%** | **-1.05%** | **-1.49%** | **-0.23%** | **0.10%** | **-1.48%** |
| | T Stat | 1.69 | -2.29 | 1.56 | -2.07 | -1.78 | -0.15 | -0.53 | -0.84 | -0.39 | 0.13 | -2.04 |
| | Winner | 2.30% | 0.52% | 0.06% | 4.24% | 1.54% | 4.96% | 4.07% | 8.21% | 2.51% | 4.44% | 1.15% |
| | Loser | 0.48% | -5.11% | 2.04% | -8.86% | -4.27% | -5.35% | -5.12% | -9.70% | -2.74% | -4.35% | -2.63% |
| 6 | **Mth Ret** | **2.51%** | **-3.45%** | **3.25%** | **-3.31%** | **-1.71%** | **0.12%** | **0.79%** | **-3.49%** | **0.48%** | **0.44%** | **-0.88%** |
| | T Stat | 3.57 | -4.02 | 7.11 | -4.57 | -2.94 | 0.14 | 1.24 | -4.96 | 1.83 | 1.10 | -2.28 |
| | Winner | 2.16% | 0.61% | -0.75% | 3.24% | -0.60% | 2.21% | 3.87% | 7.39% | 1.67% | 3.31% | 0.57% |
| | Loser | 0.35% | -4.06% | 3.99% | -6.55% | -1.11% | -2.09% | -3.07% | -10.88% | -1.19% | -2.88% | -1.45% |
| 12 | **Mth Ret** | **0.60%** | **-3.90%** | **3.34%** | **-3.14%** | **-1.14%** | **-0.74%** | **0.83%** | **-3.71%** | **-0.07%** | **-0.57%** | **-0.56%** |
| | T Stat | 1.19 | -6.27 | 11.78 | -7.14 | -3.23 | -1.68 | 2.17 | -7.65 | -0.34 | -2.08 | -2.73 |
| | Winner | 0.98% | 0.04% | -1.09% | 2.86% | -1.05% | 0.78% | 3.85% | 6.97% | 1.12% | 3.26% | 0.25% |
| | Loser | -0.37% | -3.94% | 4.42% | -6.00% | -0.09% | -1.52% | -3.02% | -10.67% | -1.19% | -3.82% | -0.81% |
| 18 | **Mth Ret** | **-0.25%** | **-3.41%** | **2.67%** | **-2.94%** | **-1.14%** | **-1.66%** | **-0.07%** | **-3.61%** | **-0.54%** | **-1.34%** | **-0.58%** |
| | T Stat | -0.62 | -6.72 | 10.52 | -7.41 | -3.67 | -4.60 | -0.23 | -9.03 | -3.57 | -6.20 | -3.38 |
| | Winner | 0.29% | -0.27% | -1.52% | 2.66% | -1.24% | 0.44% | 3.52% | 6.44% | 0.80% | 2.71% | 0.12% |
| | Loser | -0.54% | -3.14% | 4.19% | -5.60% | 0.10% | -2.11% | -3.59% | -10.06% | -1.35% | -4.04% | -0.71% |
| 24 | **Mth Ret** | **-0.05%** | **-2.08%** | **2.16%** | **-3.08%** | **-1.21%** | **-1.81%** | **-0.53%** | **-3.18%** | **-0.54%** | **-1.49%** | **-0.45%** |
| | T Stat | -0.18 | -5.46 | 10.26 | -8.63 | -4.20 | -6.32 | -1.95 | -10.99 | -4.48 | -8.80 | -2.92 |
| | Winner | 0.07% | -0.03% | -1.94% | 2.19% | -1.44% | 0.60% | 3.05% | 6.15% | 0.70% | 2.56% | 0.06% |
| | Loser | -0.12% | -2.05% | 4.10% | -5.27% | 0.23% | -2.41% | -3.58% | -9.33% | -1.24% | -4.05% | -0.51% |

## Table 5: Momentum Returns across Different Years

This table displays momentum returns by year for trading strategies with a 6 month formation period and 1, 3, 6, 9, 12, 18 and 24 month holding periods. Stocks are allocated into 10 deciles based on their past performance each Wednesday. The momentum strategy involves going long (short) on the stocks in the winner (loser) portfolio. Extremely low priced stocks (below $0.50) and illiquid (no trades within 5 days of the end of ranking period) stocks are excluded from the analysis. These trades are implemented 1 week after the ranking date. If a stock is de-listed before the end of the holding period, it is assumed that the stock is sold at the last traded price and the proceeds are invested at the risk free rate. The return of the momentum strategy is computed as the average return of the winners minus the losers. The student t-statistic adjusted for HAC errors values are shown ('T Stat').

| | | K: Holding Months | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Year | | 1 | 3 | 6 | 9 | 12 | 18 | 24 |
| 1991 | **Mth Ret** | **-7.19%** | **-4.98%** | **-0.97%** | **-0.60%** | **-2.02%** | **-2.94%** | **-4.22%** |
| | T Stat | -2.04 | -2.19 | -0.70 | -0.54 | -1.76 | -2.93 | -2.28 |
| 1992 | **Mth Ret** | **-0.50%** | **1.76%** | **0.49%** | **-0.51%** | **-0.54%** | **-1.05%** | **-0.41%** |
| | T Stat | -0.31 | 1.60 | 0.32 | -0.37 | -0.49 | -1.48 | -0.90 |
| 1993 | **Mth Ret** | **-3.77%** | **-4.73%** | **-2.62%** | **-1.46%** | **-1.50%** | **-1.38%** | **-1.27%** |
| | T Stat | -2.15 | -3.61 | -2.45 | -1.60 | -1.25 | -1.94 | -3.77 |
| 1994 | **Mth Ret** | **1.37%** | **2.31%** | **1.69%** | **1.13%** | **0.84%** | **0.60%** | **0.75%** |
| | T Stat | 1.11 | 4.42 | 7.47 | 4.56 | 4.45 | 2.97 | 5.09 |
| 1995 | **Mth Ret** | **-1.56%** | **-0.12%** | **-0.36%** | **-0.37%** | **-0.94%** | **-1.55%** | **-0.94%** |
| | T Stat | -1.37 | -0.18 | -0.92 | -1.17 | -3.60 | -5.23 | -3.98 |
| 1996 | **Mth Ret** | **1.44%** | **0.95%** | **0.78%** | **0.59%** | **0.35%** | **0.14%** | **0.01%** |
| | T Stat | 1.49 | 1.69 | 2.16 | 2.26 | 1.13 | 0.70 | 0.09 |
| 1997 | **Mth Ret** | **3.41%** | **2.68%** | **1.93%** | **1.08%** | **0.68%** | **0.37%** | **-0.65%** |
| | T Stat | 2.45 | 4.02 | 7.83 | 5.83 | 3.64 | 1.53 | -1.70 |
| 1998 | **Mth Ret** | **-2.14%** | **-0.34%** | **-0.43%** | **-1.58%** | **-2.37%** | **-5.50%** | **-6.87%** |
| | T Stat | -1.41 | -0.37 | -0.54 | -2.13 | -3.60 | -4.40 | -6.91 |
| 1999 | **Mth Ret** | **1.11%** | **0.97%** | **0.50%** | **-1.28%** | **-3.09%** | **-1.42%** | **-0.91%** |
| | T Stat | 0.66 | 0.76 | 0.48 | -1.12 | -2.29 | -2.65 | -3.06 |
| 2000 | **Mth Ret** | **1.38%** | **2.28%** | **1.96%** | **1.30%** | **1.11%** | **0.54%** | **-0.43%** |
| | T Stat | 0.45 | 1.98 | 3.74 | 3.24 | 3.37 | 2.06 | -1.77 |
| 2001 | **Mth Ret** | **0.48%** | **2.24%** | **2.41%** | **2.44%** | **2.58%** | **2.10%** | |
| | T Stat | 0.21 | 1.72 | 3.36 | 6.93 | 12.76 | 12.87 | |
| 2002 | **Mth Ret** | **1.67%** | **3.32%** | **1.62%** | | | | |
| | T Stat | 0.92 | 4.10 | 4.24 | | | | |
| Pre 1996 | **Mth Ret** | **-1.20%** | **-0.34%** | **-0.05%** | **-0.14%** | **-0.46%** | **-0.76%** | **-0.55%** |
| | T Stat | -1.65 | -0.61 | -0.10 | -0.33 | -1.10 | -2.16 | -1.78 |
| Post 1996 | **Mth Ret** | **0.89%** | **1.65%** | **1.31%** | **0.47%** | **-0.15%** | **-0.84%** | **-1.67%** |
| | T Stat | 0.94 | 2.73 | 2.95 | 1.10 | -0.36 | -2.20 | -4.95 |

**Table 6: Momentum Returns across Different Market States**

This table displays momentum returns across different market states for trading strategies with a 6 month formation period and 1, 3, 6, 9, 12, 18 and 24 holding periods. Stocks are allocated into 10 deciles based on their past performance each Wednesday. The momentum strategy involves going long (short) on the stocks in the winner (loser) portfolio. Extremely low priced stocks (below $0.50) and illiquid (no trades within 5 days of the end of ranking period) stocks are excluded from the analysis. These trades are implemented 1 week after the ranking date. If a stock is de-listed before the end of the holding period, it is assumed that the stock is sold at the last traded price and the proceeds are invested at the risk free rate. The average monthly return (Mth Ret) is reported. In Panel A, the momentum strategy is defined as being formed in a UP (DOWN) market state if the market return over the formation period is above (below) 1 standard deviation of the market's mean return. In Panel B an UP (DOWN) market state is defined market return over the formation period (past 6 months) that is above (below) an annualized return of 10%. Panel A and B reports on the value weighted excess returns for the period January 1995 to September 2002. Weights are allocated based on the size at the end of the ranking period. The student t-statistic values are shown ('T Stat'). The average monthly return of the winner portfolio ('Winner') and loser portfolio ('Loser') are shown separately.

| | | K Holding Months | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Market State | | 1 | 3 | 6 | 9 | 12 | 18 | 24 |
| Panel A: One Standard Deviation Definition | | | | | | | | |
| DOWN | **Mth Ret** | **-0.33%** | **1.24%** | **0.69%** | **1.10%** | **0.98%** | **0.70%** | **0.54%** |
| | T Stat | -0.16 | 1.20 | 1.44 | 2.87 | 4.21 | 3.43 | 2.35 |
| | Winner | 4.91% | 4.50% | 2.87% | 1.97% | 1.60% | 0.86% | 0.76% |
| | Loser | -5.24% | -3.26% | -2.17% | -0.87% | -0.62% | -0.16% | -0.21% |
| UP | **Mth Ret** | **-1.00%** | **1.41%** | **1.17%** | **1.54%** | **0.82%** | **-0.11%** | **-0.17%** |
| | T Stat | -0.38 | 1.42 | 1.57 | 2.22 | 1.52 | -0.23 | -0.55 |
| | Winner | -2.78% | -0.23% | 0.65% | 1.05% | 0.13% | -0.07% | -0.20% |
| | Loser | 1.78% | 1.64% | 0.52% | 0.49% | 0.69% | -0.04% | 0.04% |
| UP-DOWN | **Mth Ret** | **-0.67%** | **0.17%** | **0.49%** | **0.48%** | **-0.18%** | **-0.91%** | **-0.81%** |
| | T Stat | -0.28 | 0.17 | 0.76 | 0.83 | -0.41 | -2.37 | -2.73 |
| | Winner | -7.69% | -5.20% | -2.59% | -1.09% | -1.79% | -1.08% | -1.17% |
| | Loser | 7.03% | 5.37% | 3.07% | 1.57% | 1.61% | 0.17% | 0.36% |
| Panel B: Annualized Return of 10% Cutoff | | | | | | | | |
| DOWN | **Mth Ret** | **1.44%** | **1.94%** | **0.27%** | **0.92%** | **0.81%** | **0.66%** | **0.61%** |
| | T Stat | 0.54 | 1.63 | 0.42 | 2.07 | 3.98 | 2.63 | 2.00 |
| | Winner | 6.10% | 5.16% | 3.02% | 2.19% | 1.73% | 0.91% | 0.80% |
| | Loser | -4.66% | -3.22% | -2.75% | -1.27% | -0.91% | -0.25% | -0.20% |
| UP | **Mth Ret** | **3.26%** | **3.06%** | **2.39%** | **1.88%** | **1.13%** | **0.21%** | **-0.20%** |
| | T Stat | 3.61 | 6.14 | 7.42 | 7.14 | 5.15 | 1.14 | -1.48 |
| | Winner | 0.64% | 0.91% | 0.96% | 0.68% | 0.09% | -0.35% | -0.51% |
| | Loser | 2.62% | 2.15% | 1.43% | 1.20% | 1.04% | 0.56% | 0.31% |
| UP-DOWN | **Mth Ret** | **1.82%** | **1.16%** | **2.15%** | **1.02%** | **0.34%** | **-0.51%** | **-0.95%** |
| | T Stat | 0.91 | 1.26 | 4.37 | 2.78 | 1.55 | -2.14 | -3.42 |
| | Winner | -5.46% | -4.72% | -2.42% | -1.82% | -2.02% | -1.50% | -1.64% |
| | Loser | 7.28% | 5.89% | 4.57% | 2.85% | 2.36% | 1.00% | 0.69% |

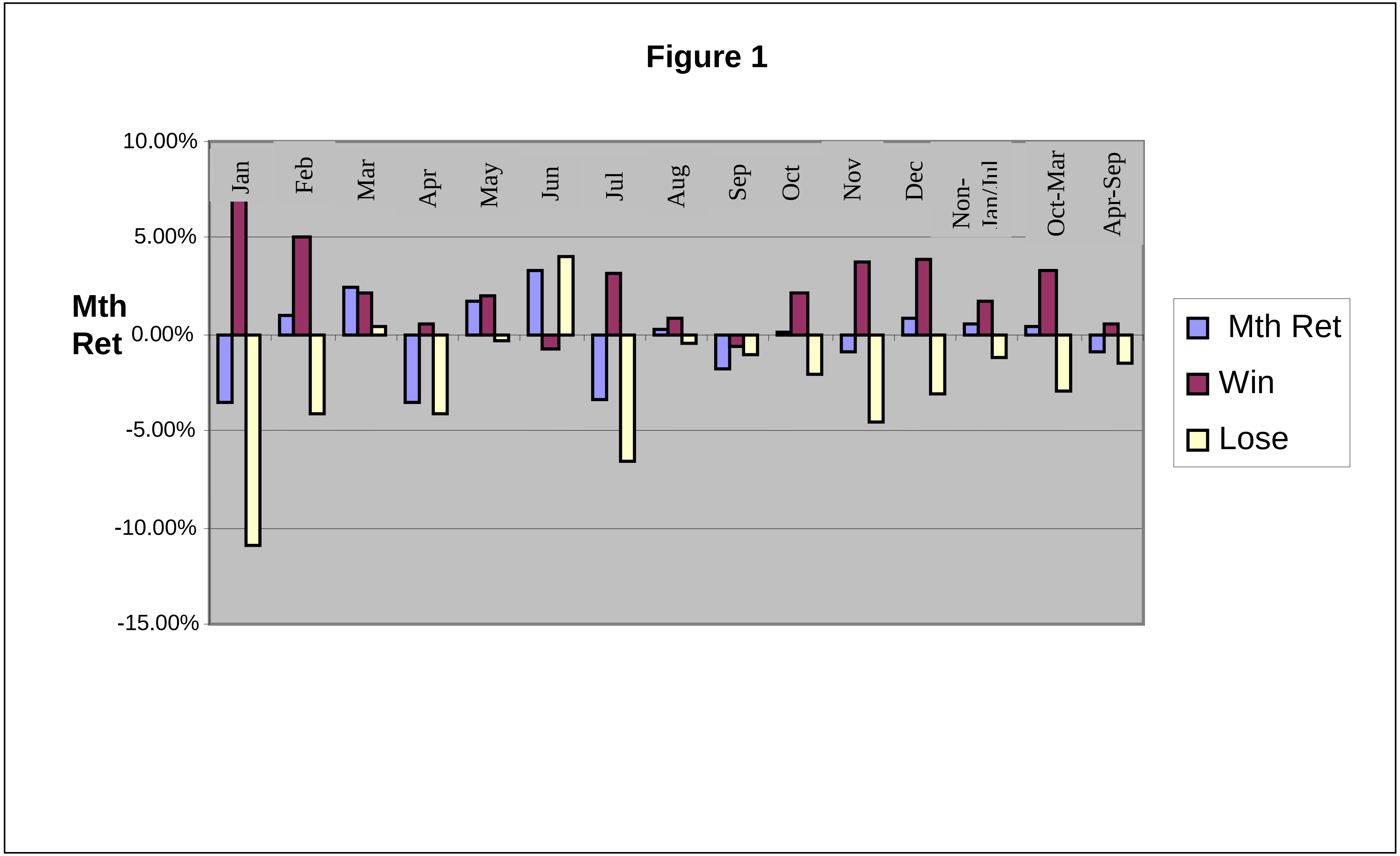


Figure 1: Average Monthly Returns for a 6-6 Momentum Strategy for each Calendar Month