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Momentum returns in Australian equities: The influences of size, risk, liquidity and return computation

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Abstract

The apparent predictability of stock prices, and the related profitability of investment strategies based on this, has generated a great deal of research. Since the late 1980s, momentum strategies have attracted considerable attention and have been found to be profitable in numerous markets. This paper investigates the returns to short-term and intermediate-horizon momentum strategies in the Australian equity market. We focus on 'practical' or 'realistic' investment strategies, and find that momentum is prevalent in the Australian market and that the returns are of greater magnitude than previously found in overseas markets. These momentum strategy returns are robust to risk adjustment and prevail over time. We also examine the interaction of momentum on size and liquidity variables and conclude that the observed profits to these investment strategies are not explained by size or liquidity differences among the stocks.

JEL classification: G12; G14
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1. Introduction

The predictability of future returns has been a controversial topic for a number of years. In a variety of studies conducted across various markets, several trading rules, employing

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momentum and contrarian strategies, have been found to be profitable for differing investment horizons.

Return predictability and evidence relating to momentum and contrarian trading are documented for many equity markets around the world, including the major US markets (NYSE, NASDAQ, AMEX), European markets, G-7[1], and Asian markets. Further, momentum in returns of other assets has also been documented. These include foreign currencies, commodities and real estate.[2]

Momentum refers to a predictable pattern in returns. More specifically, stocks with above (below) average return in recent months tend to outperform (underperform) other stocks in subsequent months. Momentum trading strategies involve taking advantage of this anomaly by purchasing stocks that have performed well and short selling those that have underperformed a common benchmark.

Equity market momentum studies can be categorized as short-term (an investment horizon of 1 week to 1 month) or intermediate-term (3 to 12 months), while in long-term studies (3 to 5 years) contrarian profits are generally documented.[3] Excess returns for US equities of around 14% per annum have been documented in short-term studies, around 12–16% per annum for the intermediate-term, and 8–9% per annum for the long-term.

An investigation of the Australian equity market provides a comparison with the US, European and Asian markets. Any similarities in results would establish evidence of common components of momentum in different markets, and possibly support the inclusion of momentum as an additional factor in asset pricing models.

This paper examines short and intermediate momentum returns for all Australian securities that are approved for short-selling or are included in the All Ordinaries Index. These selections exclude the small and infrequently traded stocks, resulting in an 'implementable trading strategy'.[4]

The main finding of this paper is that short-term and intermediate-horizon momentum is prevalent in the Australian market, and it appears to be of greater magnitude than previously found in other markets. The 'implementable' strategy we consider is not limited to particular size or time-period, nor do liquidity factors prohibit exploitation. Further, we illustrate that the results are robust to risk adjustments and that momentum profits are not compensation for risk undertaken.

[1] Which are France, UK, US, Italy, Germany, Japan, and Canada.

[2] See for example Stevenson (2002) for real estate securities, Okunev and White (2003) for foreign currencies and Taylor (1998) for commodities.

[3] The most cited and thorough examinations of short-run return predictability are Lehmann (1990) and Jegadeesh (1990). Intermediate-horizon momentum returns have been most frequently researched. The landmark paper in this area is Jegadeesh and Titman (1993). Jegadeesh and Titman (2001) investigate intermediate-horizon momentum returns in the 1990s and find strikingly similar results to the earlier study. Other papers that confirm these results are Hong et al. (2000) and Grundy and Martin (2001). For examples of long-term contrarian studies see, for example, DeBondt and Thaler (1985), Jegadeesh and Titman (2001) and Grundy and Martin (2001).

[4] We define an implementable trading strategy as one that can be applied in actual markets. The main requirements for a strategy to be implementable are that the stocks considered are highly liquid, and that there are no regulatory restrictions to short-selling. As we explain below, we choose our sample companies based on these attributes.

The remainder of the paper is organized as follows: Section 2 discusses the data, Section 3 describes the empirical design, Section 4 summarizes the results and Section 5 concludes the paper.

2. Data

The samples used for this study comprise stocks that are Approved Securities on the Australian Stock Exchange (ASX) during the period September 1990 to July 2001 and all stocks that are included in the All Ordinaries Index for the period July 1996 to July 2001. This sample contains up to 462 Approved Securities and 772 All Ordinaries stocks[5] (subsequently referred to as Index Stocks). All firms were used in the tests for the entire period they remained on the respective lists. Although the effect of survivorship bias on momentum strategies remains relatively unexplored, including all the stocks in the tests that satisfy the condition that they are Approved Securities or Index Stocks eliminates the problem, should it exist.

Daily volume weighted average prices (VWAPs) for all the stocks were calculated using SEATS data, which was obtained from SIRCA. All the additional information for the stocks; market capitalization, trading volume, relative spread and the measure used to compute excess returns; the daily return on the All Ordinaries Accumulation Index, was supplied by ASX and SIRCA.

Momentum strategies documented in the literature rely heavily on short selling stocks that are underperforming. However, there are stringent short-selling restrictions that investors must face when dealing on ASX. Past research has assumed this obstacle is nonexistent and calculated returns to momentum strategies, which are of significant value in theory, but costly or impossible to implement in practice.

Momentum analysis will also be conducted using the stocks in the All Ordinaries Index. The reasons for choosing this sample of stocks are similar: Stocks within the index are larger and more liquid than nonindex companies,[6] and accordingly a transaction intensive strategy can invest in and liquidate these without incurring high costs such as high bid–ask spread. Further, the Australian All Ordinaries Index has wide practical application. It is one of the main barometers of market activity, it is actively followed by brokers, and is widely referred to by funds and investment managers.

The use of daily VWAPs means that our calculations will be more granular than most other studies, which generally use monthly data. These studies usually attenuate the effects of bid–ask bounce and asynchronous trading by separating the estimation period and prediction period by 1 month. This is done because the month-end closing prices of winner securities are likely to be at the ask, while the closing prices of the losers are likely to be at the bid. Using VWAPs avoids this problem of bid–ask bounce.

[5] The two samples have considerable overlap because most of the Approved Securities are also Index Stocks. However, Approved Securities are not a perfect subset of Index Stocks.

[6] The criteria for the construction of the index are based on liquidity and market capitalization. For example, the minimum capitalization of a company has to be $130 million. These criteria were amended on 3 April 2000.

3. Empirical design

3.1. Momentum trading strategies

The momentum strategy used in this paper involves constructing momentum portfolios in the following manner. At the end of each K-day ($K = 30$, 60, 90, 180) estimation period, stocks are ranked in ascending order based on their buy–hold returns in excess of the market return.

The stocks are then assigned to 1 of the 10 equally weighted relative strength portfolios, where portfolio 1 represents the 'loser' portfolio with the stocks that have the lowest past K-day estimation period buy–hold excess return, and portfolio 10 represents the 'winner' portfolio with the stocks that have the highest returns. The portfolios are then held for a subsequent L-days, 'prediction period' ($L = 30$, 60, 90, 180). This gives a total of 16 momentum strategies.

Prediction period abnormal returns are measured in three ways: buy–hold returns, arithmetic returns, and logarithmic returns, all in excess of the market. We prefer buy–hold returns because they accurately reflect the actual return that investors receive from their investments. Nevertheless, logarithmic and arithmetic returns are also computed, to provide comparison to previous results. However, we are also aware of Barber and Lyon's (1997) and Kothari and Warner's (1997) preference for buy–hold returns. Barber and Lyon argue that researchers who restrict their analysis to cumulative abnormal returns could conceivably make incorrect inferences. It is important however to note that both Barber and Lyon (1997) and Kothari and Warner (1997) also outline problems associated with the use of buy–hold returns. These include a new listing bias that leads to a positive bias in the population mean, and a bias as a consequence of the 'skewness' of the buy–hold return distribution.

Because stocks come on and off both the Approved Securities and All Ordinaries Index, the decision to include a stock in the given strategies depends on whether the stock is on the list for a sufficient period of time. For a company to be considered for the strategy, it needs to be on the list for all the estimation period plus 2 days in the prediction period.[7] If a stock is partially on the list for the prediction period, the returns are calculated for the time it is on the list and the stock is assumed to be held as cash thereafter.

We examine all possible 30-day, 60-day, 90-day and 180-day estimation and prediction intervals. For example, a 30–30 strategy that starts on Day 1 includes an estimation period of Day 1–Day 30, and prediction period of Day 31–Day 60. The next 30–30 strategy covers Day 31–60 as the estimation period, and 61–90 as the prediction period, so that the prediction period of the first strategy becomes the estimation period for the second strategy.

[7] If we do not specify at least 2 days, a return cannot be calculated. There is a small number of cases (0.17%) where a stock existed for the whole of the estimation period and only 1 day of the prediction period, and thus had to be excluded from the strategy.

The significance of the various zero-cost (i.e., the portfolio that is long in the past winners and short in the past losers) momentum portfolio returns in excess of the market index are examined using a *t*-statistic.

3.2. Robustness checks

3.2.1. Size

To examine whether the profitability of the momentum strategy is confined to smaller stocks, size-neutral momentum portfolios are created by sorting stocks according to size, measured by market capitalization at the end of the estimation period. This involves creating relative strength portfolios based on past 30-, 60-, 90-, and 180-day buy–hold returns as in Section 3.1. We then form momentum quartiles based on size. That is, the 25% of stocks with the highest returns are allocated to P4, the next 25% to P3, and so on, with the worst performers allocated to P1. Then, within each quartile, stocks are ranked in ascending order into quartiles based on market capitalization. That is, portfolios are created with the smallest 25% assigned to S1, the next 25% to S2, and so on with S4 containing the largest stocks. Average buy–hold returns in excess of the market return are reported the zero-cost portfolio.

3.2.2. Liquidity

A stock is considered to be 'liquid' if the cost of buying or selling a large number of shares on demand is low, and takes a relatively short period of time. The notion that measures of liquidity can influence asset returns is now quite well accepted. In a landmark paper, Amihud and Mendelson (1986) show that market participants are willing to pay for liquidity. They measure liquidity by the quoted bid–ask spread and document that there is a positive relation between expected returns and spread. Brennan et al. (1998) demonstrate a negative relation between average returns and dollar trading volume, with the latter as their proxy for liquidity.

To examine this issue, liquidity-neutral momentum portfolios are created by sorting stocks according to liquidity, using an analogous method to the size-neutral portfolios created in Section 3.2.1. We proxy liquidity using three measures for the estimation period, average daily volume, frequency of trade and time-weighted relative bid–ask spread.[8] By examining 'liquidity-neutral' momentum portfolios, we are able to determine whether the profitability of the strategy is confined to illiquid stocks. Average buy–hold returns in excess of the market return are reported for the return to the zero-cost portfolio.

3.3. Market-adjusted model

Conrad and Kaul (1998) suggest that momentum strategies are profitable because following a momentum strategy amounts to buying, on average, high-mean risk securities

[8] Because the results for each liquidity definition are qualitatively similar, we only report the results for average daily volume. The frequency of trade and bid–ask spread results is available on request to the corresponding author.

using the proceeds from the sale of low-mean risk securities. To examine this conjecture and control for market risk using a different approach, we estimate a time-series regression for the stocks using the market model.

In estimating the market model regressions, we force the intercept (α) through zero. The stocks that performed well in the estimation period are likely to have a positive α, and the stocks that did poorly will have a negative α. If the α is not set to zero in estimating the stock β, and consequently in the calculation of excess returns, any momentum effect may be eliminated.[9]

The regression parameters are estimated during the estimation period (30, 60, 90, or 180 days) for each stock and the buy–hold excess returns in the prediction period are defined in the usual manner (i.e., the stock's actual return less [the estimated beta for the stock multiplied by the market return]).

3.4. Regression analysis

To separate the effects of size, liquidity, short and intermediate-horizon momentum returns on excess stock performance, regression analysis is employed.

We estimate

$$(R_i - R_m)_L = \alpha + \lambda \,\mathrm{return}_{Ki} + \gamma \log(\mathrm{size})_i + \phi \,\mathrm{liquidity}_i \qquad (1)$$

where $(R_i - R_m)_L$ is the prediction period abnormal return, lag return_{Ki} is the abnormal return for estimation periods of equal length to the prediction period (i.e., $K=30/L=30$, $K=60/L=60$, $K=90/L=90$ and $K=180/L=180$), $\log(\mathrm{size})_i$ is the logarithm of market capitalization as at the end of the estimation period, and $\mathrm{liquidity}_i$ is alternatively the logarithm of average daily volume during the estimation period.

The returns are measured using buy–hold returns in both the estimation and prediction period.

4. Results

This section examines the findings of our tests. Initially, in Section 4.1, the profitability of momentum strategies, size and liquidity based explanations for momentum and the impact of various return measures are discussed for Approved Securities. Because these analogous results for Index Stocks are very similar to those of the Approved Securities, we do not report them in detail. However, we report both Index Stocks and Approved Securities results in Section 4.2, which looks at a market-adjusted model for risk, and in Section 4.3 which presents the results of our multivariate regressions.

[9] Suppressing the regression intercept to zero raises issues regarding the totality of the intercepts using a multivariate framework. It is left for future research to deal with these econometric issues. For a discussion, see Gibbons (1982).

4.1. Approved Securities momentum strategy profits

Table 1 summarizes the results from our zero-cost momentum portfolios using three different return measures for each of the 16 strategies. There are three panels which report buy–hold (Panel A), arithmetic (Panel B) and logarithmic returns (Panel C).

As mentioned in Section 3.1, buy–hold returns describe accurately the return received by investors. Thus, we will concentrate our discussion on strategies using this definition of return. A comparison of the different return measures will be provided later on.

The highest monthly returns are obtained by the zero-cost strategy that selects stocks based on their returns over the previous 180 days and then holds the portfolio for 30 days ($K=180$, $L=30$), while the least successful strategy (again in terms of monthly average return) ranks stocks based on the previous month's returns and maintains this position for

Table 1
Returns to the zero-cost momentum portfolio: Approved Securities

	$L=30$		$L=60$		$L=90$		$L=180$	
	Return	*t*-statistic	Return	*t*-statistic	Return	*t*-statistic	Return	*t*-statistic
Panel A: buy–hold returns								
$K=30$	2.64 (1.88)	3.63**	5.88 (2.10)	6.09**	7.42 (1.77)	6.50**	11.61 (1.38)	7.49**
$K=60$	5.31 (3.79)	7.31**	8.16 (2.91)	8.44**	9.65 (2.30)	8.45**	14.12 (1.68)	9.11**
$K=90$	3.60 (2.57)	4.96**	8.61 (3.08)	8.91**	9.75 (2.32)	8.54**	13.71 (1.63)	8.85**
$K=180$	7.48 (5.34)	10.30**	10.28 (3.67)	10.63**	11.90 (2.83)	10.42**	14.75 (1.76)	9.52**
Panel B: arithmetic returns								
$K=30$	2.29 (1.64)	3.04**	5.20 (1.86)	5.33**	7.11 (1.69)	6.01**	11.41 (1.36)	6.94**
$K=60$	5.04 (3.60)	6.68**	7.61 (2.72)	7.80**	10.20 (2.43)	8.63**	13.96 (1.66)	8.49**
$K=90$	3.13 (2.24)	4.15**	8.40 (3.00)	8.62**	9.15 (2.18)	7.74**	13.21 (1.57)	8.03**
$K=180$	8.06 (5.76)	10.68**	10.95 (3.91)	11.23**	11.98 (2.85)	10.13**	15.30 (1.82)	9.30**
Panel C: logarithmic returns								
$K=30$	3.24 (2.31)	4.02**	6.98 (2.49)	6.50**	9.49 (2.26)	7.16**	15.12 (1.80)	8.12**
$K=60$	6.16 (4.40)	7.65**	9.62 (3.44)	8.97**	13.10 (3.12)	7.96**	18.41 (2.19)	9.90**
$K=90$	4.38 (3.13)	5.44**	10.74 (3.84)	10.01**	12.25 (2.92)	9.25**	17.56 (2.09)	9.44**
$K=180$	9.32 (6.66)	11.58**	13.27 (4.74)	12.36**	14.97 (3.56)	11.30**	19.27 (2.29)	10.36**

The zero-cost momentum portfolios are constructed in the following manner: at the end of each K-day period, all the stocks are ranked in ascending order based on their K-day buy–hold returns ($K=30$, 60, 90, and 180). The stocks are then assigned to 1 of 10 equally weighted relative strength portfolios, where 1 represents the loser portfolio (i.e., the stocks with lowest past K-day performance) and 10 represents the winner portfolio (i.e., the stocks with the highest past K-day performance). These portfolios are then held for a subsequent L-days ($L=30$, 60, 90, and 180). This gives us a total of 16 momentum strategies in operation. The total L-day profits to the momentum portfolios (winner–loser) are reported. All the numbers are in percentages, and the figure in brackets alongside each figure represents the average monthly return to the strategy. All returns are returns in excess of the market benchmark (All Ordinaries Accumulation Index). The t-statistic has been marked with a '**' to indicate significance of the measured return at the 1% significance level. Panel A reports the momentum returns during the L-day prediction period, measured using buy–hold returns, while Panels B and C report momentum profits using cumulative arithmetic and cumulative logarithmic returns.
The strategy is run on all Approved Securities for the entire 1990–2001 sample period (462 stocks).

180 days ($K=30$, $L=180$). These strategies yield 5.34% and 1.38% per month,[10] respectively. In fact, our results are generally higher than those reported by any of the previous studies. This means that not only are the strategies we examined more 'implementable', but they are more profitable too! The previous momentum literature concentrates on the $K=6$ months, $L=6$ months strategy and report monthly profits of about 1% from this strategy: Jegadeesh and Titman (1993, 2001) report profits of around 0.95% per month in the US, Rouwenhorst (1999) reports average monthly returns of around 1% for emerging markets, and Darling (2000) reports 1.03% for Australian stocks. We find that when a similar strategy is implemented on Approved Securities, it yields profits of around 1.76% per month,[11] which are highly significant at the 1% level with a t-statistic of 9.52.

One interesting observation is that the well-documented 1-month return reversion is not observed in our results. The return reversal hypothesis relates to first-order negative serial correlation in monthly stock returns, and was documented by Jegadeesh (1990) and Lehmann (1990) for US stocks. However, it was disputed by subsequent research (Lo and MacKinlay, 1990) and Conrad and Kaul (1998), and attributed to various other factors such as bid–ask bounce and asynchronous trading. If the return reversal hypothesis were true for Australian Approved Securities, then our zero-cost strategy ($K=30$, $L=30$) that buys previous months winners and sells previous months losers would not be profitable. However, this strategy yields highly significant positive returns of about 1.88% on average. This finding is intriguing because it raises the question 'Does our use of buy–hold returns and VWAPs alleviate the bid–ask effect, and remove the 'illusory' return reversal documented in the US?'

All of the zero-cost portfolios yield significant positive returns at the 1% level and all of the three return measures give essentially the same inferences.[12] However, there is a strong difference between the magnitudes of returns to the zero-cost portfolio using the three metrics. The computed arithmetic returns are smaller than the buy–hold returns in 11 out of 16 strategies, and greater in only 5 of the 16. For instance, the $K=60/L=60$ strategy yields an average monthly buy–hold and arithmetic return of 2.91% and 2.72%, respectively. All of the logarithmic returns in Panel C exceed the buy–hold returns in Panel A, and the arithmetic returns in Panel B, highlighting that computational method can make a difference. However, none of these differences in return are significant at the 5% level.

4.1.1. Size

Table 2 investigates the effect of size on momentum profits. Average monthly zero-cost portfolio returns are presented for each size quartile and for each K-day/L-day

[10] To obtain a monthly figure, we divide the total return to the strategy by the number of months. For example in a $L=30$-day period, we divide by 1.4, $L=60$ days by 2.8, $L=90$ days by 4.2, and $L=180$ days by 8.4.

[11] Darling (2000) uses a different time period (i.e., he studies the period 1972 to 2000) and a different set of firms (i.e., he uses all stocks listed on ASX). One other relevant issue is that our results are for 180 days, which is 8.4 trading months, whereas Darling's results are for a 6-month period.

[12] The results in Table 1 are equally weighted. We also calculated value-weighted returns. Because these are very similar to the equally weighted results they are not reported. These results are available on request to the corresponding author.

Table 2
Momentum returns to size-sorted portfolios: Approved Securities

		$L=30$		$L=60$		$L=90$		$L=180$	
		Return	t-statistic	Return	t-statistic	Return	t-statistic	Return	t-statistic
$K=30$	S1	2.01 (1.44)	2.39*	5.71 (2.04)	5.27**	9.21 (2.19)	7.20**	14.07 (1.68)	7.91**
	S2	2.37 (1.69)	3.47**	5.31 (1.90)	5.69**	7.84 (1.87)	6.82**	12.78 (1.52)	7.72**
	S3	2.86 (2.04)	3.39**	6.23 (2.23)	5.89**	6.67 (1.59)	5.75**	10.22 (1.22)	6.14**
	S4	0.76 (0.54)	1.52	2.19 (0.78)	3.13**	2.65 (0.63)	3.39**	5.57 (0.66)	4.92**
$K=60$	S1	4.08 (2.91)	4.85**	8.42 (3.01)	7.77**	11.23 (2.67)	8.81**	18.38 (2.19)	10.33**
	S2	3.97 (2.84)	5.81**	8.52 (3.04)	9.13**	9.37 (2.23)	8.16**	16.37 (1.95)	9.89**
	S3	5.44 (3.89)	6.55**	8.36 (2.99)	7.91**	10.16 (2.42)	8.76**	13.44 (1.60)	8.07**
	S4	2.05 (1.46)	4.09**	3.81 (1.36)	5.77**	4.63 (1.10)	5.94**	8.84 (1.05)	7.82**
$K=90$	S1	7.02 (5.01)	8.34**	13.97 (4.99)	12.89**	18.08 (4.30)	14.19**	24.06 (2.86)	13.53**
	S2	4.20 (3.00)	6.16**	7.56 (2.70)	8.10**	8.52 (2.03)	7.42**	16.98 (2.02)	10.26**
	S3	2.68 (1.91)	3.18**	6.55 (2.34)	6.20**	7.15 (1.70)	6.17**	12.87 (1.53)	7.73**
	S4	2.92 (2.09)	5.84**	4.89 (1.75)	7.41**	4.97 (1.18)	6.38**	10.24 (1.22)	9.06**
$K=180$	S1	7.21 (5.15)	8.57**	15.25 (5.45)	14.07**	19.12 (4.55)	15.00**	25.89 (3.08)	14.56**
	S2	4.37 (3.12)	6.40**	10.16 (3.63)	10.88**	10.21 (2.43)	8.89**	16.34 (1.95)	9.87**
	S3	6.04 (4.31)	7.17**	8.28 (2.96)	7.84**	8.20 (1.95)	7.07**	13.19 (1.57)	7.92**
	S4	5.80 (4.14)	11.59**	6.82 (2.44)	10.32**	6.37 (1.52)	8.18**	14.59 (1.74)	12.91**

At the end of each month, all stocks are ranked in ascending order based on their (estimation period) past K-day buy–hold returns ($K=30$, 60, 90, and 180). The stocks are then assigned to 1 of 4 equally weighted relative strength portfolios where 1 represents the loser portfolio (i.e., the stocks with the lowest K-day performance) and 4 represents the winner portfolio (i.e., the stocks with the highest past K-day performance). The stocks within each quartile are then split into four other quartiles (S1, S2, S3, and S4) based on market capitalization as at the end of the K-day estimation period. The S1, S2, S3 and S4 portfolios within each quartile refer to the stocks from smallest to largest market capitalization. This gives us 16 portfolios to examine for each K-day/L-day strategy. The zero-cost portfolio (buy–hold) return to each size subgroup is presented. Essentially, the zero-cost S1 portfolio involves buying the smallest group of best performing stocks in quartile 4, and going short in the smallest group of the poorest performers (i.e., quartile 1). All the returns are in percentages in excess of the market benchmark, and the number alongside each return is the average monthly return to the strategy. Each t-statistic has been marked with a '*' or '**' to indicate significance of the measured return at the 5% and 1% significance level, respectively.
The strategy is run on all Approved Securities for the entire 1990–2001 sample period (462 stocks).

strategy. Results illustrate that for all the strategies considered, significant (at the 1% level) positive momentum returns are observed in 15 of the 16 size quartiles (the exception is S4 for $K=30/L=30$). A few patterns emerge: the magnitude of the average monthly return to the zero-cost portfolio is generally greatest[13] for S1, the quartile containing the smallest stocks, and smallest for S4, the portfolio with the largest stocks. For example, the most successful strategy that estimates stock returns over 180 days and invests for 30 days ($K=180/L=60$) yields 13.97% (5.45% per month) and 6.82% (2.44% per month) when implemented on the smallest and largest stocks, respectively. The corresponding inner quartile returns are 10.16% for S2 and 8.28% for S3, i.e., 3.63% and 2.96% per month, respectively. This is in line with the majority of recent findings that the momentum effect is strongest in smaller stocks, and declines with increases in market capitalization.

[13] For one strategy ($K=60/L=30$) portfolios S2 and S3 actually yield the highest returns.

The difference in zero-cost momentum returns to the S1 and S4 are significant in 5 of the 16 separate tests conducted ($K=90/L=30$, $K=90$, $180/L=60$ and $K=90$, $180/L=90$). Therefore, while we reject the hypothesis of ‘no momentum returns for larger stocks (S2, S3, S4 portfolios)’, we cannot reject the hypothesis of ‘equal momentum profits to all size deciles’ for these five tests.

Another interesting observation is that the profits to the zero-cost strategy come mainly from the sell-side of the transaction in all size quartiles.[14] However, small stocks that have underperformed the market yield significantly greater negative returns than larger underperforming stocks in the subsequent investment months.

This seems to be the main reason why the zero-cost momentum strategy implemented on portfolio S1 outperforms the strategy on portfolio S4 in all tests. Further, fourth quartile S1 stocks (small stocks that have performed well over the estimation period) perform better than S4 stocks in all prediction periods, consistent with Banz’s (1981) size effect.

Critics of momentum studies claim that equal-weighted portfolios do not accurately reflect implementable strategies as it places too much emphasis on returns of small stocks. Small stocks tend to be less liquid relative to larger stocks, and therefore the assumed positions in these stocks that equal-weighting suggests cannot be achieved without inflicting significant transaction and market impact costs. To examine this issue further, and to determine whether momentum effects disappear after we account for size, value-weighted returns to relative strength portfolios were also calculated. While these are not reported in detail they indicate that smaller stocks do yield higher momentum returns than larger stocks; all K-day/L-day momentum returns decrease with value-weighting. Returns of both the winner and loser portfolios are reduced for all the strategies, but the reduction in the contribution of the sell-side to the relative strength strategy is more apparent.

4.1.2. Liquidity

Our liquidity results are presented in Table 3, which uses average daily trading volume of the stock as a proxy for liquidity. In unreported results, we find similar results for two other proxies for liquidity, namely the frequency of trading and relative bid–ask spread.

From Table 3, all K-day/L-day strategy results reject the null hypothesis of ‘no abnormal returns’, as the zero-cost relative strength portfolio yields significant returns at the 1% level in 63 of the 64 liquidity quartiles. However, we also find that the zero-cost momentum strategy is more profitable when implemented on firms with low trading volume than firms with high trading volume in all K-day/L-day tests. For instance, over a 30-day estimation and 180-day investment period, the average return for V1 quartile (stocks with the lowest average daily trading volume) is 9.00%, whereas the same strategy yields 5.69% for the V4 quartile (stocks with the highest average daily trading volume). The difference between respective momentum portfolios is significant for 10 out of the 16

[14] These results are not reported in detail. They are available on request to the corresponding author.

Table 3
Momentum returns to volume partitions: Approved Securities

		$L=30$		$L=60$		$L=90$		$L=180$	
		Return	*t*-statistic	Return	*t*-statistic	Return	*t*-statistic	Return	*t*-statistic
$K=30$	V1	2.19 (1.56)	2.98**	4.72 (1.69)	5.04**	5.84 (1.39)	5.12**	9.00 (1.07)	5.59**
	V2	1.48 (1.06)	2.33*	4.35 (1.55)	5.09**	4.69 (1.12)	4.53**	7.42 (0.88)	5.11**
	V3	0.57 (0.41)	0.97	2.79 (1.00)	3.48**	3.19 (0.76)	3.17**	5.10 (0.61)	3.45**
	V4	1.57 (1.12)	2.51*	3.37 (1.20)	3.93**	3.89 (0.93)	3.82**	5.69 (0.68)	4.10**
$K=60$	V1	4.35 (3.11)	5.91**	8.32 (2.97)	8.90**	8.32 (1.98)	7.30**	14.79 (1.76)	9.19**
	V2	3.15 (2.25)	4.96**	4.99 (1.78)	5.84**	3.80 (0.90)	3.67**	8.52 (1.01)	5.86**
	V3	2.29 (1.64)	3.93**	4.96 (1.77)	6.19**	6.57 (1.56)	6.55**	10.88 (1.30)	7.36**
	V4	3.01 (2.15)	4.83**	3.18 (1.14)	3.70**	4.90 (1.17)	4.81**	4.40 (0.52)	3.17**
$K=90$	V1	5.26 (3.76)	7.15**	8.04 (2.87)	8.60**	8.69 (2.07)	7.62**	14.29 (1.70)	8.88**
	V2	3.18 (2.27)	5.01**	5.51 (1.97)	6.44**	7.82 (1.86)	7.56**	15.14 (1.80)	10.42**
	V3	3.45 (2.46)	5.92**	5.70 (2.04)	7.12**	8.11 (1.93)	8.07**	11.04 (1.31)	7.46**
	V4	2.44 (1.74)	3.91**	5.98 (2.14)	6.97**	6.49 (1.55)	6.37**	7.81 (0.93)	5.63**
$K=180$	V1	4.43 (3.16)	6.02**	9.17 (3.28)	9.81**	11.99 (2.85)	10.52**	18.31 (2.18)	11.38**
	V2	4.73 (3.38)	7.44**	7.92 (2.83)	9.26**	9.68 (2.30)	9.36**	14.07 (1.68)	9.67**
	V3	3.55 (2.54)	6.09**	4.52 (1.61)	5.64**	5.36 (1.28)	5.33**	3.67 (0.44)	2.48**
	V4	6.08 (4.34)	9.74**	5.99 (2.14)	6.99**	5.58 (1.33)	5.48**	6.41 (0.76)	4.62**

At the end of each month, all stocks are ranked in ascending order based on their (estimation period) past K-day buy–hold returns ($K=30$, 60, 90, and 180). The stocks are then assigned to 1 of 4 equally weighted relative strength portfolios where 1 represents the loser portfolio (i.e., the stocks with the lowest K-day performance) and 4 represents the winner portfolio (i.e., the stocks with the highest past K-day performance). The stocks within each quartile are then split into four other quartiles (V1, V2, V3, and V4) based on average daily trading volume during the K-day estimation period. The V1, V2, V3 and V4 portfolios within each quartile refer to stocks with smallest to largest trading volume. This gives us 16 portfolios to examine for each K-day/L-day strategy. The zero-cost portfolio (buy–hold) return to each volume subgroup is presented. Essentially, the zero-cost V1 portfolio involves buying the best performing stocks in quartile 4 with the lowest volume, and going short in the group of poor performers with the lowest volume (i.e., quartile 1). All the returns are in percentages in excess of the market benchmark, and the number alongside each return is the average monthly return to the strategy. Each *t*-statistic has been marked with a '*' or '**' to indicate significance of the measured return at the 5% and 1% significance level, respectively.
The strategy is run on all Approved Securities for the entire 1990–2001 sample period (462 stocks).

strategies considered.[15] Therefore, while we can conclude that the 'momentum effect' cannot be entirely explained by the 'liquidity effect', we note that there are significant differences in the sources and the magnitude of returns for each liquidity portfolio.

4.2. Risk-adjusted returns

Table 4 presents the summary statistics obtained from our risk-adjusted returns for each 30-, 60-, 90- and 180-day period. Each beta estimate calculated during the estimation period was used in the calculation of excess returns in the subsequent prediction period.

[15] Specifically, the difference between V1 and V4 is significant for $K=90/L=30$, $K=60$, $180/L=60$, $K=60$, 90, $180/L=90$ and for all $K/L=180$ portfolios.

Table 4
Risk-adjusted average returns to the zero-cost portfolio (buy–hold): Approved Securities (Panel A) and Index Stocks (Panel B)

	$L=30$		$L=60$		$L=90$		$L=180$	
	Return	*t*-statistic	Return	*t*-statistic	Return	*t*-statistic	Return	*t*-statistic
Panel A: Approved Securities								
$K=30$	2.58 (1.84)	3.32**	5.50 (1.96)	5.28**	7.60 (1.81)	6.05**	11.18 (1.33)	6.50**
$K=60$	5.85 (4.18)	7.54**	9.22 (3.29)	8.86**	10.86 (2.59)	8.64**	14.78 (1.76)	8.58**
$K=90$	3.89 (2.78)	5.01**	8.87 (3.17)	8.52**	10.18 (2.42)	8.10**	14.45 (1.72)	8.40**
$K=180$	7.65 (5.47)	9.86**	9.83 (3.51)	9.45**	11.64 (2.77)	9.26**	14.48 (1.72)	8.41**
Panel B: Index Stocks								
$K=30$	4.54 (3.24)	3.03**	7.62 (2.72)	3.25**	10.89 (2.59)	3.09**	7.53 (0.90)	5.22**
$K=60$	7.10 (5.07)	4.74**	10.77 (3.85)	4.59**	12.21 (2.91)	3.47**	10.28 (1.22)	1.42
$K=90$	5.88 (4.20)	3.93**	11.50 (4.11)	4.90**	17.36 (4.13)	4.93**	22.59 (2.69)	3.12**
$K=180$	10.19 (7.28)	6.81**	9.90 (3.54)	4.22**	11.53 (2.75)	3.27**	2.65 (0.32)	0.37

The zero-cost momentum portfolios are constructed in the following manner: at the end of each K-day period, all the stocks are ranked in ascending order based on their K-day buy–hold returns ($K=30$, 60, 90, and 180). The stocks are then assigned to 1 of 10 equally weighted relative strength portfolios, where 1 represents the loser portfolio (i.e., the stocks with lowest past K-day performance) and 10 represents the winner portfolio (i.e., the stocks with the highest past K-day performance). These portfolios are then held for a subsequent L-days ($L=30$, 60, 90, and 180). This gives us a total of 16 momentum strategies in operation. The total L-day profits to the momentum portfolios (winner–loser) are reported below. All the numbers are in percentages, and the figure in brackets alongside each figure represents the average monthly return to the strategy. All returns are calculated by subtracting the market return multiplied by the stock's beta from prediction period returns. (The market benchmark is the All Ordinaries Accumulation Index.) Each t-statistic has been marked with a '**' to indicate significance of the measured return at the 1% significance level. The strategy is run on all Approved Securities (Panel A) for the entire 1990–2001 sample period (462 stocks) and on all 772 Index Stocks (Panel B) for the period 1996–2001.

The excess returns for both the Approved Securities and the Index Stocks are strikingly similar to the figures obtained without the risk adjustment. All of the returns to relative strength portfolios of Approved Securities are significant at the 1% level. For example, the $K=30/L=30$-day strategy yields average total return of 2.64% (1.88% per month) before the risk adjustment (from Table 1). The corresponding figure in Table 4 after the risk adjustment is 2.58% (1.84% per month). The general pattern that emerges is identical to the pattern observed in Table 1 results. Momentum profits appear to slightly decrease in magnitude with a decrease in estimation period, with the most profitable strategy being the $K=180/L=30$-day investment horizon (5.47% per month).

Similarly, the returns to zero-cost portfolios constructed from the Index Stocks sample display the same features after taking each stock's estimated market beta into account. Initially, all the strategies except for the $K=30$, 60, $180/L=180$ days had significantly positive returns (not reported). After the adjustment, all of the strategies still yield positive returns (significant at the 1% level) with only $K=60$, $180/L=180$ having positive but insignificant returns.

Therefore, we reject the hypothesis that 'momentum returns are compensation for risk' for both samples.

4.3. Regression results

Finally, we examine the influence of size, liquidity and estimation period excess returns on prediction period excess returns in the same regression. This allows us to observe which of these variables contributes the most to momentum returns. Table 5 shows that for both of our samples, and for all strategies (except the $K=180/L=180$-day for the Index Stocks) the coefficient for the lagged return variable is positively significant at the 1% level. For example, looking at the parameter estimates of the $K=90/L=90$-day strategy for Approved Securities, it can be seen that a 1% increase in the estimation period return results in a 0.128% increase in the prediction period excess returns. These results indicate that the momentum effect is not subsumed by the size or liquidity effect. In fact, in almost all of the strategies considered here, estimation period returns are more significant than the well-documented size or liquidity variables. Once again, the result of significant momentum in future returns is inconsistent with efficient markets.

There are several other aspects of the results that are worth noting. Firstly, the size of the lagged variable coefficient is in line with the momentum profits documented in Section

Table 5
Regression estimates for Eq. (1): Approved Securities (Panel A) and Index Stocks (Panel B)

Period	Intercept	Return	Size	Volume	R^2	Number of observations
Panel A: Approved Securities						
30–30	−0.204 (−1.69)*	0.037 (3.09)**	0.012 (10.78)**	−0.003 (−4.00)**	0.019	7397
60–60	−0.331 (−1.88)*	0.142 (8.09)**	0.018 (8.74)**	0.004 (2.88)**	0.049	3537
90–90	−0.055 (−1.53)	0.128 (6.11)**	0.030 (9.39)**	−0.008 (−1.18)	0.067	2382
180–180	−0.068 (−2.53)**	0.080 (2.77)**	0.061 (8.90)**	−0.018 (−3.63)**	0.080	1137
Period	Intercept	Return	Size	Liquidity	R^2	Number of observations
Panel B: Index Stocks						
30–30	0.015 (0.620)	0.063 (6.47)**	0.003 (1.88)*	0.004 (3.72)**	0.006	10210
60–60	−0.036 (−0.66)	0.082 (5.68)**	−0.001 (−0.36)	0.005 (2.31)*	0.008	5153
90–90	−0.137 (−2.54)**	0.046 (3.59)**	0.005 (1.630)	0.003 (1.230)	0.004	6164
180–180	−0.173 (−1.25)	0.007 (0.37)	0.009 (1.230)	−0.001 (−0.16)	0.001	2613

Coefficient estimates are obtained from pooled OLS regressions using daily stock price data. The coefficient estimates have been adjusted for heteroscedasticity and autocorrelation using the Newey–West method. The dependent variable is the prediction period excess (buy–hold) returns and the independent variables are the estimation period excess (buy–hold) returns, logarithm of market capitalization and logarithm of average daily trading volume during the estimation period. Excess returns are simply defined as return on the stock minus the return on the market. The estimated regression can be expressed as: $(R_i - R_m)_L = \alpha + \lambda \text{ lag return}_{Ki} + \gamma \log(\text{size})_i + \phi \text{ liquidity}_i$. To keep tractability, equal estimation and prediction period (i.e., $K=L$) returns have been computed. All stocks with volume data from the original samples are included in the regressions. Number of observations used to estimate each regression is given in column seven. The numbers alongside each parameter coefficient refer to the t-statistic for the estimate. t-statistics of significant estimates have been marked with '*' and '**' to indicate significance at the 5% and 1% level, respectively.

The coefficients of α, λ and γ have also been calculated using time-series averages of cross-sectional regressions. The time series considered were the 30-, 60-, 90-, and 180-day prediction periods for the entire sample period. The results obtained were similar to the above estimates and thus are not reported here.

4.1. For instance, the $K=180/L=180$ strategy yields positive but insignificant returns when implemented on Index Stocks. Analogously, the lagged return variable in our $K=180/L=180$-day regression is also positive but insignificant. Second, the intercept of the regression is negative in majority of the cases. This indicates that we expect a negative bias in the prediction period excess returns, i.e., we expect them to be less than the estimation period excess returns.

Thirdly, when we computed the F-tests for each regression (not reported) in order to test the overall significance of the equation, we found that the F-tests strongly reject the hypothesis that all the coefficients are equal to zero.

Finally, the coefficients of average daily volume are negative with the inclusion of all three variables in the regressions for the Approved Securities. This is due to the high degree of correlation between daily volume and size. A similar effect was observed in Brennan et al. (1998) when they included firm size and dollar trading volume in their regressions.

Therefore, we strongly reject the hypothesis that the momentum effect is subsumed by the size effect.

5. Conclusion

This paper documents return continuation in the Australian market during the period September 1990 to July 2001. The focus has been on 'practical' or 'implementable' momentum investment strategies. For this reason, Approved Securities, stocks that may be short sold without incurring large costs, and Index Stocks, the more liquid ASX-listed Stocks, have been examined. We have found that a trading rule that goes long in the previous 30, 60, 90 and 180 days' winners and shorts the losers yields significant profits in excess of the market up to 180 trading days after the investment trigger. These excess returns range from 5.34% to 0.46% per month, depending on the estimation/prediction period chosen. They are higher than previous findings in other US and European markets, as well as a strategy implemented in the Australian market with all the ASX stocks considered for portfolio formation (Darling, 2000). This shows that the short to intermediate-horizon investment strategy presented in this paper is not only a more 'realistic' approach to investing in the market, but it is also more profitable.

We find that return continuation is present in both small and large firm samples, is robust to risk adjustment, and is not solely attributed to extreme decile performance. Although small stocks appear to exhibit greater momentum, significant returns are found in all subsets. Further, the returns to our zero-cost strategy cannot be explained by the 'liquidity effect'. Contrary to expectations, the relative strength strategy implemented on 'illiquid' stocks yields lower (and in some cases negative returns) returns than when the strategy is applied to more liquid stocks.

There are several things that remain to be done. The notion of 'implementable' momentum strategies needs to be explored further for both the Australian and other stock markets. A follow-up of this study could examine the issue of trading costs by taking the liquidity of the stock into consideration. This would involve building the dynamics of the trading process into the portfolio accumulation and realization strategies. This could be done by fully exploiting the rich data available within the SEATS database. At this stage, we have not incorporated order flow, the depth of the bid and ask schedules, and market impact costs into our analysis.

Another interesting extension of the momentum literature could look at computing the most profitable relative strength portfolio. The common strategy that has been explored in the literature involves partitioning stocks into deciles, and going long in the top decile and short in the bottom decile. Future research could explore other combinations of investment strategies that incorporate inner decile portfolios.

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