Do Momentum Strategies Work?:

- Australian Evidence

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<u>Abstract</u>

This paper investigates the profitability of momentum investment strategy and the predictive power of trading volume for equities listed in the Australian Stock Exchange. Recent research finds that momentum and trading volume appear to predict subsequent returns in U.S. market and past volume helps to reconcile intermediate-horizon "under reaction" and long-horizon "overreaction" effects. However, bulk of the evidence on this important relationship between past returns and future returns is limited to U.S. portfolios.

This study provides an out of sample evidence by examining the relationship between "trading volume" (measured by the turnover ratio) and "momentum" strategies in an Australian setting. We document a strong momentum effect for the Australian market during the period 1988 through 2002 and find that momentum plays an important role in providing information about stocks. We also find that past trading volume predicts both the magnitude and persistence of price momentum. In summary, our findings are consistent with the U.S. evidence.

1. Introduction

An enormous body of empirical research over the past 15 to 20 years has demonstrated evidence against the prediction of the Sharpe (1964), Lintner (1965) and Black (1972) Capital Asset Pricing Model (CAPM). This evidence suggests that the cross-section of expected stock returns are not sufficiently explained by their beta, the systematic risk of CAPM. The results indicate that variables such as firm size (Banz, 1981), earnings yield (Basu, 1977), leverage (Bhandari, 1988), the firm's book value of equity to its market value (Chan, Hame and Lakonishok, 1991) and momentum (Jegadeesh and Titman 1993, Lee and Swaminathan, 2000) and more recently idiosyncratic volatility (Malkiel and Xu 1997, 2000) adequately explain the cross-section of average stock returns. This paper extends the methodology of Lee and Swaminathan (2000) to the Australian market. The motivation

comes from the fact that the bulk of existing research relates to the United States and there is very little evidence from markets outside the United States.

Jegadeesh and Titman (2001, p 699-700) state *"The criticism that observed empirical regularities arise because of data mining is typically the hardest to address because empirical research in non-experimental settings is limited by data availability. Fortunately, with the passage of time, we now have nine additional years of data that enable us to perform out-of-sample tests as well as to assess the extent to which investors may have learned from the earlier return patterns".*

In this paper we provide out-of-sample evidence by investigating the momentum strategies for equities listed in the Australian Stock Exchange. In addition, our objective is also to provide academic researchers and investors with a greater breadth and depth of understanding of the anomalies discovered in the area of empirical finance. Most research on the profitability of momentum strategies is based on U.S. data, particularly for the NYSE stocks[1]. For instance, Jegadeesh and Titman (1993) report that strategies that buy past winners and sell past losers realize significant abnormal returns over the 1965 – 89 periods. Conrad and Kaul (1998) argue that momentum profits arise because of cross-sectional differences in expected returns rather than time-series return patterns. Barberis et al. (1998), Daniel et al. (1998), and Hong and Stein (1990) present behavioral models which suggest that the post holding period returns of the momentum portfolio should be negative. Jegadeesh and Titman (2001) find that the momentum profits in the eight years subsequent to their 1993 period are similar to the profits in the earlier period. Thus, they argue that momentum profits cannot be due to data snooping biases.

Chordia and Shivakumar (2002) argue that profits to momentum strategies can be explained by a set of lagged macroeconomic variables and payoffs to momentum strategies disappear once stock returns are adjusted for their predictability based on these macroeconomic variables. There is also some evidence on momentum suggesting that bulk of the observed

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[1] Jegadeesh and Titman (1993) find that when stocks are selected based on their past six month return and held for six months they realize a return of over 12 percent per annum.

momentum in U.S. individual stock returns is an industry effect. (See, for example, Moskowitz and Grinblatt (1999) and O'Neal (2000)).

Rouwenhorst (1998) and Dijk and Huibers (2002) provide evidence for European price momentum in the intermediate-horizon. Chan et al. (2000) examine the momentum effect based on individual stock market indices in 23 countries. They also find statistically significant evidence of momentum profits. However, Hameed and Kusnadi (2002) suggest that the factors that contribute to the momentum phenomenon in U.S. are not prevalent in the Asian Markets.

It is a well accepted fact that trading volume plays a minor role in conventional models of asset prices. However, recent research shows that past trading volume provides an important link between "momentum" and "value" strategies (Lee and Swaminathen, 2000; Connolly and Stivers 2003). Several papers suggest that past trading volume may provide valuable information about a security. For instance, Lamoureux and Lastrapes (1994) examine the ability of volume data to shed light on the source of persistence in stock-return volatility. They find that the dynamics of daily return variance are due solely to daily persistence in the latent speed of arrival of information to the market, which leads to similar dynamics in the level of trading volume. Blume et al. (1994) present a model in which traders can learn valuable information about a security by observing both past price and past volume information. However, their model does not specify the nature of the information that might be derived from past volume.

In a similar vein, Lee and Swaminathan (2000) find that the effect of momentum appears more pronounced among high-volume stocks than low-volume stocks. They show that trading volume is only weakly correlated with traditional liquidity proxies and that the volume effect is robust to various risk adjustments. However, Scott et al. (2003) propose that the predicting power of the price momentum and trading volume is a result of the under reaction

of investors to earnings news – an effect that is most pronounced for high-growth companies. Wang (1994) suggests that the dynamic relation between volume and returns varies depending upon the motive for trading by the " informed investors".

Wang (1994) also states that momentum in consecutive returns is likely if the primary motive for the informed investors' trading in the former period has better information about the stock's fundamentals. Conversely, a reversal is likely if the primary motive for the informed investors' trading in the former period is changes in their outside investment opportunities.

In light of these findings, this paper attempts to examine the relationship between "trading volume" (measured by the turnover ratio) and "momentum" strategies for Australian equities. The study of markets outside the US is interesting since our objective is to provide an out of sample evidence on the interaction between momentum strategies and future returns. Our findings show a strong momentum effect in Australian market during the period 1988 through 2002 and it plays an important role in providing information about stocks. Consistent with Lee and Swaminathan (2000), when conditional on past returns we find that low volume stocks generally do better than high volume stocks over the next 12 months. The price momentum premium is higher in median and low volume stocks. The remainder of this paper is organised as follows. The next section deals with the data and portfolio aggregation procedures. Section 3 presents the findings while section 4 concludes the paper.

2. Data and Methods

Our sample consists of stocks listed on the Australia Stock Exchange during the period June 1988 through May 2002 with at least a year of data prior to the portfolio formation date. Monthly stock and market returns, number of shares outstanding and traded and value of shares traded are obtained from the database maintained by the Securities Industry Research Center of Asia Pacific (SIRCA). We divide the sample into two periods because of

data limitations. The first period is from June 1988 to May 1995. In this period we only have returns data for our sample. There are 296 eligible stocks in this period. This sample provides some useful information about the momentum effect.

The second period is from June 1995 to May 2002. This sample has available information on past returns, trading volume, market capitalization, and stock prices. It is used to test the relationship between trading volume and "momentum" strategies. Trading volume is defined as the average monthly turnover in percentage during the portfolio formation period, where monthly turnover is the ratio of the number of shares traded each month to the number of shares outstanding at the end of the month. There are 165 stocks that match the criteria.

We follow the approach of Lee and Swaminathan (2000) in constructing our portfolios. At the beginning of each month, all eligible stocks are ranked independently on the basis of past returns and past trading volume. The stocks are then assigned to one of five portfolios based on returns over the previous J months (where J=3, 6, 9 or 12) and one of three portfolios based on trading volume over the same period. All stocks are ranked in ascending order, so the top quintile based on the past return is the loser quintile and the bottom is the winner quintile. Similarly, the top treble based on the past volume consists of low volume stocks and the bottom consists of high volume stocks. The intersections resulting from the two independent rankings result in to 15 momentum-volume portfolios. In each month the strategy buys the winner portfolio and sells the loser portfolio in each volume group. We focus our attention on monthly returns of extreme winner and losers over the next K months (where K = 3, 6, 9 or 12) and next 5 years.

Similar to Jegadeesh and Titman (1993) and Lee and Swaminathan (2000), the monthly return for a K-month holding period is based on an equal-weighted average of portfolio returns from strategies implemented in the current month and the previous K – 1 months. For example, the monthly return for a three-month holding period is based on an equal-

weighted average of portfolio returns from this month's strategy, last month's strategy, and strategy from two months ago.

3. Findings

In this section the results for price momentum and volume-based price momentum strategies and the information content of trading volume are presented. Recall that our main objective is to examine the relationship between "trading volume" (measured by the turnover ratio) and "momentum" strategies in an Australian setting.

3.1 Momentum strategies

At the beginning of each month, we rank all eligible stocks independently on the basis of past returns. The stocks are then assigned to one of five portfolios based on returns over the previous J months (J=3, 6, 9 or 12). In each month we long the winner portfolio and short the loser portfolio. This section reports the returns of the portfolio strategies described above over the two periods: from 1988 to 1995 and from 1995 to 2002. We report results for the top quintile portfolio of extreme losers (R1), the bottom quintile of extreme winners (R5), and one intermediate portfolio (R3). Our findings show a clear momentum effect in both sample periods.

Table I reports the results for the first sample period. Columns 4 through 7 report equal-weighted average monthly returns over the next K months (K=3, 6, 9, 12). In addition, for each portfolio formation period (J) and holding period (K), we report the mean return from a dollar-neutral strategy of buying the extreme winners and selling the extreme losers (R5 – R1). For example, with a six-month portfolio formation period (J=6), past winners gain an average of 1.37 percent per month over the next six months (K=6). Past losers lose an average of 1.51 percent per month over the same time period. The difference between R5 and R1 is 2.88 percent per month. The differences in average monthly returns between R5 and R1 are significantly positive in all (J, K) combinations.

The last five columns of Table I report the annual event-time returns for each portfolio for five 12-month periods following the portfolio formation date. We find that momentum effect last until four years when portfolios are formed on past three months returns. The R5 – R1 portfolio yields a statistically significant positive return until year four. For other portfolios, we document a reversal in the sense that R5 – R1 is not statistically significant beyond year one (where J=6, 9 and 12). Nearly all R5 – R1 portfolios yield statistically insignificant returns, except for portfolio based on past 6-month returns. We also find that when portfolios are based on past 12-month returns, R5 – R 1 returns are negative post year one but significant in years four and five. Exhibit 1 shows this pattern graphically. Portfolio based on past 12-month returns becomes loser in year 2. However, portfolio based on past 3-month returns is still a winner, although the abnormal return is much smaller and not statistically significant. Our findings in this respect are consistent with Lee and Swaminathan (2000) who find that "the longer the estimation period for past returns, the more imminent the future price reversals" (Lee and Swaminathan 2000, 2026).

Table II reports the results from the second time period, 1995 to 2002. The findings are similar to those from the first period. In addition, we also find that extreme price momentum portfolios exhibit higher trading volume. For example, the average monthly turnover for the R1 and R5 portfolios in the nine-month portfolio formation period is 2.2 percent and 3.8 percent respectively. However, the average turnover for the intermediate (R3) portfolio is only 1.5 percent. Lee and Swaminathan (2000) find that trading volume is positively correlated with absolute returns and this positive relation is asymmetric. Similar to Lee and Swaminathan (2000), we also find asymmetry in the positive relation between absolute returns and trading volume in the sense that extreme winners have a higher trading volume than extreme losers. Overall, our findings are consistent with prior research in this area.

3.2 The relationship between volume and momentum strategies

Table III reports portfolio returns over the next K months (where K=3, 6, 9, 12) where portfolios are formed on the basis of a two-way sort between price momentum and past trading volume. We follow the approach of Lee and Swaminathan (2000) and sort all stocks at the beginning of each month based on their returns over the past J months and divide them into 5 portfolios (R1 to R5). We then independently sort the same firms based on their average monthly turnover rate over the past J months and divide them into three volume portfolios (V1 to V3). V1 represents the lowest trading volume portfolio, and V3 represents the highest trading volume portfolio.

The results from Table III show that conditional on past returns low volume stocks usually generate high returns than high volume stocks over the next 12 months. The returns of V3 – V1 portfolios are almost all negative. There are some positive returns for the V3 – V1 portfolio, however, they are all in the 3 month holding period (K=3) and not statistically significant. All the (J, K) combinations (except K=3) have similar results. We find that low volume losers (R1V1) lose less than high volume losers (R1V3) in the next 12 months. Low volume losers earn an average return between –2.3 percent and 0.07 percent per month. High volume losers earn an average return between –4.2 percent and –1.2 percent per month. For example, for J=9, K=9, low volume losers outperform high volume losers by 1.3 percent per month, although they are all losers with negative returns. The differences between low volume losers and high volume losers are almost all statistically significant.

The return differential between high and low volume winners is similar. Low volume winners (R5V1) earn an average return between 1.1 percent and 3.6 percent per month, while high volume winners (R5V3) earn an average return between –1.0 percent and 3.1 percent per month. In sum, we confirm that stocks that experience low trading volume in the recent past tend to outperform stocks that experience high trading volume.

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Our findings are consistent with Lee and Swaminathan (2000) in this respect. They interpret this as evidence that low volume firms command a greater illiquidity premium. According to the liquidity hypothesis, the portfolio with lower liquidity should earn higher expected returns. However, Lee and Swaminathan also find the price momentum premium is higher in high volume firms which is presumably more liquid. In this paper, we find similar results to those of Lee and Swaminathan's for portfolios based on past three and six month returns. Interestingly, for portfolios based on past nine and twelve-month returns, the findings are opposite, that is, we find that price momentum premium is higher in low volume firms.

The bottom row of each combination in Table III shows the return to a dollar-neutral price momentum strategy (R5 – R1). For example, for J=3 and K=6, the price momentum spread is 4.1 percent for high volume firms and only 2.7 percent for low volume firms. The difference of 1.4 percent is statistically significant. However, the findings in the portfolios that are based on past nine and twelve-month returns are different in the sense that they support the liquidity hypothesis. For example, for J=12 and K=12, the price momentum spread is only 0.29 percent for high volume firms and 1.1 percent for low volume firms. The difference of 0.81 percent is also statistically significant. Our findings contradict Lee and Swaminathan (2000) and Scott et al. (2003) who find that price momentum is more pronounced among high volume stocks. Thus, it is our conjecture that the price momentum premium depends on the portfolio formation period.

3.3 Further tests

Table IV reports further tests conducted on these basic intermediate-horizon results. In this table we report results for the six-month and nine-month formation period (J=6, J=9)[2]. Recall that the results are based on five price momentum and three trading volume portfolios (5 * 3). Table IV shows that the results are similar when we change the construction of the

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[2] The results of portfolios based on past three and twelve month returns are similar to those based on past six and nine month returns.

portfolios. Panel A reports results using three price momentum and five trading volume portfolios (3 * 5), whereas Panel B reports results using three price momentum and three volume portfolios (3 * 3). Generally, Table IV shows that low volume stocks outperform high volume stocks for almost all portfolios. Price momentum is more pronounced among high volume stocks over 12 months for portfolios based on past six-month returns. For example, in panel A, for J=6, K=9, the momentum spread is 1.7 percent for high volume stocks and only 0.99 percent for low volume stocks. This effect could be driven by low volume losers who gain 0.3 percent per month and high volume losers who lose 1.6 percent per month. For portfolios that are based on past nine-month returns the results are mixed.

The price momentum premium is higher in high volume stocks when the holding period is short, but lower or disappearing when the holding period increases. For example, in panel A, J=9 and K=3, the difference in momentum premium between V5 and V1 is 0.86 percent per month. However, when K=12 the difference is –0.56 percent per month. The actual reason for this phenomenon is not clear, however, it is suggested that the magnitude of price momentum premium not only depends on the portfolio formation period, but also on the holding period.

3.4 Findings over next five years

Table V reports descriptive characteristics for various price momentum and volume portfolios. We find that low volume stocks tend to be much small and have higher price. For example, Panel A shows that low volume winners (R5V1) have a median price of $2.05 while high volume winners (R5V3) have a median price of $0.95. Lee and Swaminathan (2000) find that high volume stocks are more highly priced in U.S. In contrast, Australian stock prices are generally much lower than those in U.S. Since the Australian stock market is much smaller than the U.S. market, the existence of some difference between different countries is inevitable.

Table VI presents long-term annual returns to various trading volume and price momentum portfolios over the next five years. These results are based on the six- month portfolio formation period (J=6), five momentum portfolios, and three volume portfolios (5 * 3). Year 1 through 5 represent the monthly returns of each portfolio in the five twelve month periods following the portfolio formation date. Panel A presents raw returns while Panel B reports size-adjusted returns. Once again we follow Lee and Swaminathan (2000) in constructing our portfolios. The size adjustment is based on equal weighted size decile portfolios. Each stock's size adjusted return is computed by subtracting the monthly return of the appropriate size portfolio from the individual stock's monthly return. Monthly size adjusted portfolio returns are computed as an equal weighted average of the adjusted returns of individual stocks.

Exhibit 2 provides graphical representations of long-term monthly returns of buying winner and selling loser strategies (R5 –R1) over the next five years after the portfolio formation date. It can be observed clearly that the spread between winners and losers (R5 – R1) is higher for low volume stocks. We also can see this through the bottom row of each panel of Table VI. . For example, in Panel A, the momentum spread for high volume stocks is 0.12 percent per month and 0.24 percent per month lower than those of low volume stocks in Year 1. In addition, we find that the price momentum effect disappears after 12 month of the formation date for high volume stocks. However, the effect exists until year 4 for low and medium volume stocks. After year 4 the momentum effect disappears for all three groups. In contrast, Lee and Swaminathan (2000) find that high-momentum stocks with high volume tend to subsequently outperform high momentum stocks with low volume.

The last five columns of Table VI report the difference between high and low volume stocks (V3 – V1), controlling for price momentum. The results show that low volume stocks outperform high volume stocks for each of the next five years. This is another difference between the Australian market and the U.S. market. Lee and Swaminathan (2000) find this

effect for low volume losers whereas we find it for all low volume stocks. Since it is argued that trading volume may be a proxy for firm size effect we conduct the same test after adjusting for firm size. The results in Panel B show a similar pattern. Although size adjustment decreases price momentum returns for high and medium volume portfolios, the adjustment has no effect on the volume results. Exhibit 3 shows that low volume firms continue to outperform high volume firms in the next five years even after size adjustment. Thus, trading volume does not appear to be a proxy for firm size. Once again our findings are consistent with that of Lee and Swaminathan (2000).

3.5 Price reversals, volume and momentum strategies

Lee and Swaminathan (2000) find that price reversals are more pronounced among low volume losers (R1V1) and high volume winners (R5V3). Price momentum is more pronounced among high volume losers (R1V3) and low volume winners (R5V1). It can be seen that low volume losers have negative returns before they begin to earn positive returns after twelve months. In the U.S., low volume losers begin to have positive returns only after Year 1[3], which is one year later than in Australia[4]. Similarly, high volume winners begin to have negative returns one year early in Australia than in the U.S. Low volume winners in Australia always have positive and significant returns over the next five years while in the U.S. they become losers after Year 3. Overall, the results confirm the findings of Lee and Swaminathan (2000) and that in fact that the momentum effect is stronger in Australia.

We now proceed to test the two volume based price momentum strategies suggested by Lee and Swaminathan (2000). The first strategy is called early-stage strategy, which involves buying low volume winners and selling high volume losers. The stocks in these portfolios usually experience price momentum over a longer period. The second strategy is late-stage

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[3] See Lee and Swaminathan (2000).

[4] The comparison is made on size adjusted returns for both countries.

momentum strategy which means buying high volume winners and selling low volume losers and price momentum in these stocks should reverse faster. We test these two strategies by using raw data as well as size adjusted data.

Table VII shows the annual returns of the simple price momentum strategy (simple), early-stage strategy (early) and late-stage strategy (later). We follow the approach of Lee and Swaminathan (2000) and adopt these strategies for comparison purposes. Panel A shows that simple strategy earns 0.28 percent to 0.33 percent per month in the first 3 years before the momentum disappears. The late strategy immediately begins losing in year one. In contrast, the early strategy earns significant positive returns for all five years.

When we compare these two strategies with the simple strategy, we find that early momentum strategies earn significantly higher returns in each of the next five years. However, late momentum strategies earn significantly lower returns in all of the five years. Exhibit 4 shows that the size adjusted results are similar to that draw from the raw data. Price momentum and price reversal are more pronounced in Australia. The momentum premium for early strategies lasts longer than that in the U.S.

Exhibit 4 also shows that both long-horizon under reaction and overreaction can occur in different volume portfolios. Lee and Swaminathan (2000) suggest that if we only look at the returns for late stage stocks in isolation, it will be obvious that price momentum is an overreaction to fundamental news. The momentum premium disappears and the stocks in these portfolios begin losing and continue to lose in the next five years. If we only look at the returns for early stocks in isolation, it shows that price momentum is the effect of market under reaction. Lee and Swaminathan (2000) argue that "both effects are part of a more general process by which information is incorporated into prices" (Lee and Swaminathan 2000, 2045). Our results support this view. In an interesting paper Moskowitz and Grinblatt

(1999) suggest that a portion of the returns from momentum strategies is due to industry effects. However, we are unable to test this argument because of data limitations.

3.6 Can volume predict future returns?

We find trading volume, as measured by the turnover ratio, provides important information about price momentum and can be used to predict future returns. However, it is to be noted that the explanation of the usefulness of trading volume is controversial. For instance, Wang (1994) develops an equilibrium model of stock trading and suggests that trading volume conveys important information about how assets are priced in the market. Wang (1994) also assumes a world with two types of investors: agents with superior information and uninformed investors. In this economy, informed investors trade for informational and no informational purposes. Wang (1994) suggests that when informed investors' condition their trades on private information high future returns are expected when they are accompanied by high trading volume.

In contrast, Campbell et al. (1993) present a model in which risk-averse utility maximizers act as market makers for liquidity or noninformational investors in a world of symmetric information. In their model, if liquidity traders sell, causing a drop in stock prices, then risk-averse utility maximizers might act as market makers but would require a higher expected return. Thus, they predict that price changes with high volume will more likely to be reversed. However, we document mixed results. Table VI shows that high volume winners do reverse which supports Campbell et al (1993). On the other hand, low volume losers also have fast reversal, which supports the findings of Wang (1994). Thus, we are of the view that trading volume contains some information not captured by these two models. Another school of thought is that trading volume can act as a proxy for liquidity. In this paper we use turnover ratio as the proxy for volume. Lee and Swaminathan (2000) argue that although average daily dollar volume is a proxy for liquidity, the average daily turnover is not necessarily a liquidity proxy. Liquidity refers to the ability to buy or sell a stock at close to its market price.

Liquidity has some existing proxies, such as volume, volatility, and number of trades. It also can be measured through the bid-ask spread or changes in market depth. Size, or the market value of the stock, is also related to liquidity since a larger stock issue has smaller price impact for a given order flow and a smaller bid-ask spread. However, we use turnover ratio as a measure of liquidity in the spirit of Datar et al. (1998). The following table reports cross-sectional Spearman rank correlations of trading volume to firm size and stock price. It shows that trading volume (as measured by average monthly turnover) is not highly correlated with size and stock price.

	Firm Size	Stock Price
Turnover	0.338	0.093

To better understand the role of the trading volume in providing information to stock returns, we form portfolios based on price momentum and changes in trading volume following Lee and Swaminathan (2000). In Table VIII, we replicate the long term return prediction tests, replacing trading volume with the actual change in trading volume. To construct this table, stocks are independently sorted into five momentum portfolios and three portfolios based on changes in trading volume over the past one year (ΔV). We define the 12-month period just prior to the portfolio formation date as year t, then the change in volume as the average monthly turnover over the past six months minus the average monthly turnover in year $t - 1$ ($\Delta V = V(6, t) - V(t - 1)$).

This is different from Lee and Swaminathan's approach. In their study they choose a four-year horizon instead of one year. In this study we only have seven years of data with all available information and thus, if we choose a four-year horizon it would result in too few eligible observations. For the same reason, we reduced the long term returns to four years,

because there are not enough observations in year five. We document a positive relationship between the level of trading volume and the change in trading volume, although not very strong. The Spearman rank correlation between these two variables is 0.342.

Table VIII shows that portfolios ranked on price momentum and changes in trading volume exhibit similar patterns in future returns as those ranked on price momentum and level of trading volume, except for the losers with the least increase (or the most decline) in volume. For example, momentum premium is high in low volume stocks and stocks with the least increase (or the most declines) in volume. There is no momentum effect in stocks with high volume and stocks with the most increase in volume. The last four columns show that stocks with the least increase (or the most declines) in volume outperforms stocks with the most increase in volume with the exception of the losers. When low volume losers begin to earn positive returns, losers with least increase in volume are still losing money and continue to lose even after four years.

3.7 Further test of Momentum Life Cycle of Lee and Swaminathan (2000)

Lee and Swaminathan (2000) develop an interesting explanation for the findings in their study. This is the Momentum Life Cycle (MLC) hypothesis. It presents the interaction between price momentum, reversals, and trading volume in a single framework. We apply this hypothesis to our findings and find that our results support this hypothesis.

According to the Momentum Life Cycle, stocks experience different periods of investor favoritism and neglect. High volume winners and low volume losers as late stage momentum stocks are more likely to reverse in the near future. Conversely, low volume winners and high volume losers as early stage momentum stocks are more like to persist in the near future. These phenomena are more pronounced in our findings. For late stage momentum stocks, they reverse faster compared to stocks in Lee and Swaminathan's (2000) study, usually after 12 months. For early stage momentum stocks, they persist longer (in all the

next five years). Lee and Swaminathan (2000) suggest that trading volume may help locate a given stock in the momentum life cycle and provide information about market sentiment of the stock. They argue when a stock is popular to the investors, its trading volume increases as well; when it is no longer popular, the trading volume decreases with the popularity. Thus, trading volume may provide useful information when making investment decisions.

4. Conclusion and final remarks

In this paper we investigate the profitability of momentum strategies in an Australian setting. We find substantial momentum in monthly stock returns during the period 1988 to 2002. Various formations and holding periods are used to form momentum strategy portfolios. The abnormal returns from these portfolios vary from 0.3 percent per month to 7 percent per month in the intermediate horizon. The price momentum reversal reported in Lee and Swaminathan (2000) is confirmed here. However, the speed of the reversal in Australia is much slower than in the U.S. That is, in the U.S. most of the momentum effects reverse after one year, but they last three to four years in Australia before disappearing. Moreover, we also find that the speed of the reversal depends on the formation period, with longer formation period leading to quick reversal.

In addition, we also confirm Lee and Swaminathan's (2000) findings that trading volume provides information about the magnitude of momentum profits. Our findings show that momentum spread (R5 – R1) is larger for high volume portfolios in the intermediate horizon, which is consistent with the findings of Lee and Swaminathan (2000). However, in the long horizon, we find that high-momentum stocks with low volume tend to outperform high momentum stocks with high volume, which contradicts prior research. It is not clear whether this effect is due to possible differences between Australian and U.S. stock markets. We also examine the early stage strategy and late stage strategy advanced by Lee and Swaminathan (2000). Since the momentum effect reversal in Australia is slower than in the U.S., we argue

that these strategies will be of use to Australian investors. When early strategy is applied, the momentum profit can be earned for four years instead of three years in U.S.

Evidence also shows that trading volume is not highly correlated with firm size and stock price. Our size adjusted results support the role of the trading volume in predicting future returns. Our findings support the liquidity hypothesis when portfolios are formed on past nine and twelve month returns. All other results contradict the liquidity hypothesis. Moreover, further tests show the results from portfolios based on past nine and twelve-month returns are not reliable enough to fully accept the liquidity hypothesis. Our findings show the Momentum Life Cycle (MLC) works quite well in the Australian setting. In addition, we also document that trading volume provides useful information in predicting future returns. As far as the MLC hypothesis is concerned we are of the view that further research should be conducted to investigate this interesting phenomenon.

Our results also raise some questions for future research in the sense that the returns reported in this paper are gross returns. That is, our returns are not adjusted for transaction costs. Jegadeesh and Titman (1993) suggest that in the U.S. the transaction cost of 0.5 percent per trade is conservative. However, the transaction costs in Australia may be different from those in U.S. In addition, our findings only partially fit the behaviour models. For example, according to Hong and Stein (1999), the momentum effect would be more likely among low volume stocks because of the insufficient diffusion of information resulting from scarcity of trading. This is only true for portfolios based on past 9 and 12 months returns in our study. For other portfolios, the price momentum strategies perform better among high volume stocks. Nevertheless, we find a strong momentum effect in Australian equities and also that trading volume plays an important role in providing information about stocks.

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