Financial Innovation

RESEARCH Open Access

Industry- and liquidity-based momentum in Australian equities

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Abstract

This study examined momentum profitability in Australia, providing further evidence for intermediate-term momentum profitability. Using data spanning different market states, we found that momentum was stronger after the global financial crisis. We also examined industry-level momentum strategies and found strong evidence for industry momentum. Specifically, industries that perform well relative to other industries continue to outperform others while those that underperform continue to perform poorly. This finding suggests the exploitability of return continuation and profit-making opportunities for traders at the industry level. Regarding liquidity, we found that it has no clear predictive power for momentum returns. Hence, our results do not appear to support the conjecture that liquidity can be a determining factor for momentum profitability in Australia.

Keywords: Momentum strategy, Stock momentum, Industry momentum, Liquidity, Market states, Australia

Introduction

A momentum trading strategy is a technical analysis tool frequently used by practitioners. Here, traders simultaneously consider long stocks that have outperformed in the recent past and short stocks that have underperformed. The belief is that stock price movement will continue in the same direction over the short term to the medium term. Hence, traders can make abnormal profits by extrapolating previous price trends. The first paper to formally document momentum evidence was Jegadeesh and Titman (1993). They found that buying winning stocks and selling losing stocks in the US market could generate an annualized return of 12.01%. Much work has been done since on the effect of momentum in the US and other markets. Prior work has shown that the momentum effect is predominantly positive and significant in developed markets such as in the US and Europe while the effect is more elusive in others, especially in emerging markets.

Momentum is now a well-known anomaly, and the strategy has been popular among traders. Notably, although many so-called anomalies, such as the small-firm effect, dissipated after being reported, momentum has shown staying power more than two decades after its formal documentation. Yet, the reason for its persistence is not clear. One way to investigate whether the momentum effect is truly an anomaly rather than an artifact of data mining is to examine different data sets that have either not been previously researched or have produced contradictory results. If momentum can be shown to be prevalent across markets—even those of different calibers—it may be considered a systematic risk factor, and its exposure should be compensated in the form of different mean returns. As implied by the adaptive markets hypothesis (Lo 2004), as well as subsequent research in the same vein (Shi and Zhou 2017), the performance of trading strategies may change over time due to time-varying and path-dependent risk premiums. This implies that traders need to adapt to changing market conditions to achieve better performance.

While stock price momentum is well documented in the US and Europe (Jegadeesh and Titman 1993; Rouwenhorst 1998), evidence is mixed in some other markets. In Malaysia, Tan et al. (2014) found that momentum strategies afforded small but statistically reliable profits. Demirer et al. (2015) reported the presence of a momentum anomaly in the Chinese stock market and documented a significant herding effect on the short-run performance of momentum trading strategies. Shi et al. (2015), meanwhile, found contrary evidence of short-term and long-term contrarian profitability. While one may ascribe the inconsistent evidence for momentum in emerging markets to retail investor profiles (which is counterintuitive since emerging markets are presumably less efficient), it is noteworthy that another developed market—Australia—has also shown contradictory momentum evidence. As a developed market in the Asia-Pacific region, Australia is an attractive investment destination for international investors. Given its robust political and economic standing, it is home to many major multinational financial service providers. With more data available now, it is worth investigating and reexamining the mixed evidence for momentum issues in this market. This will not only shed more light on momentum issues in Australia but also provide a broader global perspective on this anomaly.

This study examined momentum issues in Australian equities for the period 1995–2014. This period spans two major financial crises and enables the examination of different time periods. This made it possible to scrutinize momentum patterns across different market states, in particular, the global financial crisis, something not already examined in earlier studies. We first investigated the efficacy of a broader investment strategy that utilizes Australian equities, regardless of industry classification and firm-specific characteristics. This provided an overall framework to facilitate a subsequent investigation of style investing, which entailed dividing sample stocks into portfolios of different styles based on firm-specific characteristics, such as liquidity or segregating stocks on the basis of industry sector. Additionally, stocks in the same industry tend to move together as they are subjected to the same business cycles and driven by the same underlying factors. Therefore, understanding whether the return continuation effect is persistent when stocks are sorted by industries/sectors provides further evidence for the robustness of the momentum effect. Third, we explored the profitability of liquidity-based momentum strategies. We examined whether considerable profits can be reaped when liquidity-conscious portfolio construction is considered. While many studies have examined the relationship between liquidity and expected returns, less work has been done on the predictive power of liquidity measures for the momentum effect. In this analysis, we used bid-ask spread as a proxy for liquidity and stratified portfolios based on liquidity level. The initial conjecture was that larger-spread stocks lead to stronger momentum since there is an empirically established positive relationship between expected return and bid-ask spread (Amihud and Mendelson 1986). The rest of this paper is organized as follows. Next, we discuss the related literature. The section after that provides details about our sample and method. Then, the empirical results are presented and discussed. The last section concludes the paper with a summary of the evidence.

Related research

The momentum effect was found to be pervasive in the US equity market and in European equities (Jegadeesh and Titman 1993; Rouwenhorst 1998). In Australia, the evidence is mixed. Hurn and Pavlov (2003) documented a strong momentum effect using 200 Australian stocks from 1973 to 1998. Phua et al. (2010) studied the properties of momentum trading strategies using daily stock data from 1991 to 2002 and reported the existence of the momentum effect in Australia. Their analysis revealed some qualitative differences between US momentum and Australian momentum. Most notably, small firms were found to display greater momentum in the US whereas in Australia, larger companies exhibited a stronger momentum effect. Brailsford and O'Brien (2008) concurred with Phua et al. (2010). In particular, they found that momentum was evident only in the 500 largest stocks, and mid-cap stocks exhibited the most economic significance. Demir et al. (2004) found that not only are momentum strategies profitable in Australia but the returns are also of greater magnitude (the most successful strategy yielded 5.34% per month) compared to other markets. They also argued that size and liquidity differences among stocks could not explain the observed momentum profits in Australia. Notably, the strategy tested by Demir et al. (2004) was the more "implementable" one—the underlying sample consisted of Approved Securities (up to 462 stocks) during the period September 1990 to July 2001 and all of the stocks in the All Ordinaries Index for the period July 1996 to July 2001. In addition, their sample period included a sustained bull market that could have greatly enhanced the overall profitability of the strategies. Another study that used a "more realizable" strategy is Vanstone et al. (2012). They examined the momentum profitability of constituent stocks of the S&P/ASX100 during the period 2000–2011 and reported positive momentum evidence. Using the S&P/ASX200 index from 2000 to 2007, Galariotis (2010) reported positive and significant monthly returns, ranging from 1.58% to 2.70%. Bettman et al. (2009) examined momentum strategies in Australian stocks and verified the significance of momentum profitability, consistent with Demir et al. (2004).

Not all of the momentum studies of the Australian stock market have reported positive evidence. Durand et al. (2006) reported an absence of a momentum effect in their study period (1980–2001). Their research design closely matched that of Jegadeesh and Titman (1993) in that all of the stocks listed on the Australian stock exchange for the study period were included in the sample. Durand et al. (2006), meanwhile, contradicted the findings of Demir et al. (2004), considering that the research periods of the two studies had nearly 10 years of overlap. The authors attributed the contradictions to methodological differences between the two studies. Similarly, Griffin et al. (2003) reported no or weak evidence of momentum profits in Australia. They examined momentum evidence in 40 countries and found only weak and statistically unreliable momentum in most emerging markets and in Australia. The aforementioned studies suggest that the evidence for momentum in Australia is sensitive to variations in stock coverage and in time periods (Brailsford and O'Brien 2008).

Some studies have used industry membership as a grouping criterion to explain momentum. Moskowitz and Grinblatt (1999) found that industry momentum strategies are more profitable than stock momentum strategies. Demirer et al. (2015) found that in China, industry herding has a positive influence on industry momentum. Other studies corroborating this evidence include Du and Denning (2005) and O'Neal (2000). Not all of the research ascribes the stock momentum effect to industry influence. For example, Grundy and Martin (2001) argued that these two phenomena are essentially distinct from one another. Similarly, Nijiman et al. (2004) contended that the individual stock effect plays a more important role than industry influence in European stocks. Chen and Demirer (2018) reported a lack of momentum effect in industry returns in Taiwan but documented a profitable herding-based momentum strategy. Chen et al. (2017) explored how oil price dynamics affect stock market momentum in China. They found that oil price dynamics can be exploited to devise active management strategies. Li et al. (2014) assessed industry momentum in Australia using the constituent stocks of the S&P/ASX200 index and found strong evidence of stock-level momentum; however, they reported relatively smaller industry-level returns. Put differently, they found no evidence of stock momentum being subsumed by industry effects. In an attempt to refine stock and industry momentum strategies, Safieddine and Sonti (2007) focused on industry growth instead of industry per se and reported higher momentum returns for stocks belonging to high-growth rather than mature industries. The logic is that high-growth industries are usually associated with greater uncertainty and mispricing; hence, a more pronounced momentum effect should be observed with this kind of industry. However, the authors found no evidence that stock momentum is an industry phenomenon.

Constructs that have been commonly used to predict future stock returns include trading volume and turnover, which act as alternative proxies for liquidity. The conventional liquidity explanation suggests a negative relationship between liquidity and a stock's expected return. That said, relatively few studies have paid attention to the predictive power of liquidity measures on the momentum effect. Among them, Demir et al. (2004) found that momentum profitability in Australian could not be explained by liquidity. Li et al. (2009) found that in the UK, trading volume was negatively related to momentum profitability. Tan et al. (2018) reported that price momentum strategies work better among higher-liquidity stocks. On the contrary, Lee and Swaminathan (2000) tested the volume-based momentum strategy and found a stronger momentum effect among high-volume stocks. This result is counterintuitive to the conventional liquidity hypothesis. In response, the authors argued that the information content inherent in trading volume caused the seemingly counterintuitive result. Lee and Swaminathan (2000) thus argued that trading volume contains information, and information content is related to investors' misperceptions of a firm's future earnings prospects. Therefore, the more ambiguous the information environment of a firm's valuation, the more disagreeable investors are regarding its intrinsic value, and hence the greater the turnover. Such a case results in more severe mispricing and therefore stronger momentum. Presenting similar evidence, Chan et al. (2000) used 17 international stock market indices and reported higher profits for stocks with higher trading volume. Based on the above, it seems that there is an inconclusive directional relationship between liquidity and the momentum effect. Notably, Lee and Swaminathan

(2000) argued that trading volume is an unlikely proxy for liquidity due to its low correlation with the common proxies of market liquidity, such as firm size and relative bid-ask spread. Blume and Keim (2012) contended that share turnover is an "imprecise and indirect measure" of liquidity (p. 4). Accordingly, we used bid-ask spread to shed light on the limited liquidity-momentum literature and examine the relationship between liquidity and the momentum effect.

A related research domain involves decision-making methods. This includes behavior monitoring methods Chao et al. (2019), group decision-making (GDM) models (Zhang et al. 2019; Li et al. 2018), and multiple criteria decision-making (MCDM) models (Kao et al. 2014; Kao et al. 2012). Kao et al. (2014) argued that MCDM tools can contribute to the quality of financial decision-making processes as well as the resulting decisions themselves. Their work demonstrated why financial decision problems should be considered MCDM problems and presented an MCDM-based approach that ranked popular clustering algorithms in the area of financial risk analysis. Their results showed the effectiveness of their methods for evaluating clustering algorithms. Recently, Kao et al. (2019) extended such work to the domain of financial systemic risk. The present study of momentum profitability may be considered a relevant extension to complex decision processes since we examine momentum profitability under different criteria—namely, industry differences and the liquidity characteristics of stocks.

Data and method

Data

We extracted stock prices for the period September 1995 to September 2014 from Datastream. To construct our underlying sample, we first included the constituent stocks of the All Ordinaries Index, which is a broad market index representing the 500 largest companies in Australia. This way, we could ensure that the more investable stocks were covered. The remaining sample of stocks were selected in a random manner. In addition, all of the foreign stocks listed in the local bourse were excluded. To mitigate survivorship bias, we did not intentionally omit companies that were delisted during the study period. When stock price values were missing because of nontrading periods, the values were left blank and not substituted with any preceding observations to avoid any artificial sense of strong return continuation. Following the above selection criteria, we constructed an underlying sample of 772.

The Industrial Classification Benchmark (ICB) was adopted to uniformly classify stocks into industries. The ICB system is a four-tier industry classification method, and each tier divides the market into increasingly specific sectors. In this system, each stock is uniquely classified into 10 industries, which are further partitioned into 16 supersectors. The supersectors are further divided into 41 subsectors, which contain 114 sectors. This study applied the second level of classification. We partitioned the entire market into 19 supersectors instead of other narrower industry definitions to ensure having a reasonably sufficient number of stocks in each industry portfolio.

Method

We used the portfolio-based approach of Jegadeesh and Titman (1993) to construct momentum portfolios. To form winner and loser portfolios, an underlying sample of stocks was sorted into terciles or quintiles based on the individual stock's past J-month lagged returns. The J-month lagged return is hence the formation period (hereafter, denoted as J), which would be 3, 6, 9, or 12 months. Once the stocks were sorted, they were ranked in ascending order based on their past J-month cumulative returns. The winner portfolio comprises stocks with the highest past J-month returns whereas the loser portfolio consists of stocks with the lowest past returns. All of the portfolios are equally weighted. The constructed portfolios would then be held (i.e., long winners and short losers) for K subsequent months where K equals 3, 6, 9, or 12 months. This way, we generated 16 momentum trading strategies. Following conventions in the literature, we skipped 1 month between J and K to attenuate microstructure issues such as the short-run stock return reversal effect. To illustrate the abovementioned portfolio construction, a three-month formation and three-month investment period strategy (J3/K3) were considered. At the end of each month, all of the stocks were ranked in ascending order on the basis of their past three-month average monthly returns. The top performers represent the winner portfolio, and stocks that underperformed denote the loser portfolio. A month was skipped before the investment period of the subsequent 3 months. Since this study used monthly returns, when the investment period exceeded 1 month, an overlap in the investment period returns was inevitable. Hence, we constructed overlapping portfolios to increase the power of the test. Thus, in any given month *t*, the strategies hold a series of portfolios that are selected the month before (due to the one-month lag) as well as in the previous K - 1 months, depending on the strategies adopted. As a result, we formed K-composite portfolios, each of which was initiated 1 month apart. The above describes the research design for forming the winner portfolio. An analogous approach was adopted to construct the loser portfolio. Finally, momentum returns were computed as the difference between the returns of the winner and loser portfolios. A test of significance was then carried out to determine the statistical reliability of the spread—that is, the momentum return. As a robustness check, we also computed risk-adjusted returns using the Sharpe measure. The Sharpe measure is computed as excess returns scaled by standard deviation. We used the three-month T-bill rate to obtain excess returns.

The method for constructing industry momentum portfolios was similar to that of Moskowitz and Grinblatt (1999). First, we aggregated sample stocks into specific industries as defined by the ICB second-level classification, which would generate 16 industry portfolios in total. Subsequently, industry portfolios were sorted into quintiles based on their past J-month returns. The top 20% of industries were assigned to the winner industry portfolios, and the bottom 20% were sorted into the loser industry portfolios. The long position was taken for the winner industry portfolios whereas the short position was taken for the loser industry portfolios for K months after a one-month lag. This interindustry approach generated 16 strategies. As an alternative approach, we also formed industry-neutral portfolios for the four industries that either contained the greatest number of stocks or were the most profitable. To establish the importance of industry effect in explaining momentum, this study identified the winner and loser portfolios for each industry group. In this approach, we treated each of the four industries as independent sample pools. If the momentum effect dissipated after the industry effect was controlled for, the industry component could be deduced to constitute one of the sources of the momentum effect.

Stock liquidity indicates the level of investor interest in a stock. The three commonly used liquidity constructs are trading volume, share turnover, and bid-ask spread. Most previous research analyzing the relationship between momentum and liquidity has used trading volume and turnover as proxies for liquidity. However, these prior studies offer inconclusive evidence. Additionally, it has been suggested that trading volume might not be a good proxy for liquidity (Lee and Swaminathan 2000; Blume and Keim 2012). In this analysis, we used bid-ask spread as a proxy for liquidity. To form the sample pool, we excluded all of the observations with a negative or an extremely large spread for obvious reasons: zero spread denotes perfect liquidity, which may be too idealistic, and a very large spread implies that illiquidity is too high. Stocks that are overly illiquid are beyond practical usefulness for investors; hence, we omitted these stocks from our sample pool. To construct liquidity-sorted momentum portfolios, we sorted stocks into five segments according to their levels of liquidity. Specifically, sample stocks were divided into five categories: the lowest 20% as the high-liquidity group (small-spread group) and the highest 20% as the low-liquidity group (large-spread group). Within each spread group, all stocks were ranked in ascending order according to their past J-month lagged performances. The remaining procedures are analogous to the earlier steps. This procedure was repeated for each spread group, one at a time. If a significant momentum return was identified even after liquidity was controlled for, the relationship between liquidity and the momentum effect may not be established. By contrast, if varying degrees of momentum profit with meaningful statistical significance were identified after liquidity was controlled for, we may argue for some meaningful relationship between the two constructs.

Results and discussion

Stock momentum

Table 1 shows that momentum returns were mostly positive when sample stocks were divided by the tercile sorting method. In this sorting procedure, all of the strategies yielded positive returns except for J9K12, J12K9, and J12K12, and 13 of the strategies produced profits that were significant at either 1% or 5%. Among all strategies, J3K3 was the most profitable and yielded monthly returns of 0.72% (9.05% per annum). On the quintile grouping basis, 14 of the 20 strategies produced positive returns, of which 8 were statistically significant. As in the tercile sorting method, J3K3 was the most profitable strategy, yielding a momentum return of 0.66% per month (8.24% per annum).

Regardless of sorting method, we observe some stylized facts about profitability. When stocks were ranked on the basis of short-to-medium-term horizons (3 and 6 months), momentum strategies performed better and generated better returns. Furthermore, a monotonic decline in momentum returns was observed as the holding period increased. Overall, the tercile sorting style yielded better returns in terms of economic magnitude and statistical significance as compared to the quintile sorting style.

This study's results contribute to evidence for positive momentum in Australia. The profits obtained in this study are similar to those in Phua et al. (2010) but smaller in magnitude than in other Australian studies. This disparity could be due to differences in the coverage of sample stocks and in the study period. Notably, previous Australian studies that found large momentum benefits primarily used large stocks or the

Table 1 Returns of Momentum Strategies (September 1995 to September 2014)

Strategy	Panel A (3-quantiles)				Panel B (5-quantiles)			
	Winner	Loser	Winner-Loser		Winner	Loser	Winner-Loser	
J3K3	0.0202	0.0136	**0.0066**	***	0.0187	0.0115	**0.0072**	***
	5.96	*3.68*	*3.77*		*5.97*	*3.44*	*5.08*	
J3K6	0.0202	0.0156	**0.0047**	***	0.0185	0.0136	**0.0049**	***
	7.87	*5.38*	*3.92*		*7.90*	*5.22*	*4.96*	
J3K9	0.0205	0.0166	**0.0040**	***	0.0183	0.0145	**0.0038**	***
	9.60	*6.83*	*4.38*		*9.65*	*6.61*	*5.04*	
J3K12	0.0193	0.0176	**0.0017**	***	0.0175	0.0152	**0.0024**	***
	10.70	*8.58*	*2.76*		*10.93*	*8.32*	*4.40*	
J6K3	0.0195	0.0136	**0.0059**	***	0.0183	0.0123	**0.0060**	***
	5.69	*3.57*	*2.74*		*5.86*	*3.60*	*3.43*	
J6K6	0.0195	0.0153	**0.0043**	***	0.0182	0.0138	**0.0044**	***
	7.43	*5.19*	*2.84*		*7.72*	*5.21*	*3.45*	
J6K9	0.0186	0.0163	**0.0023**	**	0.0174	0.0148	**0.0026**	***
	8.43	*6.72*	*2.21*		*9.00*	*6.81*	*2.97*	
J6K12	0.0172	0.0174	−0.0001		0.0164	0.0157	0.0007	
	9.16	*8.60*	*−0.18*		*9.85*	*8.73*	*1.04*	
J9K3	0.0197	0.0142	**0.0055**	**	0.0185	0.0130	**0.0055**	***
	5.63	*3.71*	*2.49*		*5.87*	*3.74*	*2.90*	
J9K6	0.0183	0.0159	0.0024		0.0172	0.0146	**0.0026**	*
	6.94	*5.42*	*1.54*		*7.27*	*5.44*	*1.94*	
J9K9	0.0169	0.0172	−0.0003		0.0162	0.0157	0.0005	
	7.80	*7.21*	*−0.27*		*8.31*	*7.21*	*0.54*	
J9K12	0.0149	0.0187	**−0.0038**	***	0.0150	0.0169	**−0.0019**	**
	8.01	*9.52*	*−4.34*		*8.92*	*9.43*	*−2.57*	
J12K3	0.0173	0.0155	0.0017		0.0176	0.0136	**0.0039**	**
	4.93	*4.08*	*0.78*		*5.53*	*3.97*	*2.13*	
J12K6	0.0160	0.0168	−0.0008		0.0161	0.0154	0.0007	
	6.02	*5.82*	*−0.54*		*6.69*	*5.80*	*0.58*	
J12K9	0.0142	0.0184	**−0.0042**	***	0.0150	0.0167	−0.0017	
	6.49	*7.92*	*−3.59*		*7.48*	*7.82*	*−1.79*	
J12K12	0.0129	0.0193	**−0.0064**	***	*0.0139*	*0.0178*	**− 0.0039**	**
	6.88	*9.92*	*−6.82*		*8.20*	*10.05*	*−5.08*	

Note: Sample stocks were sorted into either 3 or 5 quantiles based on past J-month returns. After a one-month gap, a long position was taken for the winners and a short position for the losers. Winner minus loser represents momentum returns. The t-statistics are italicized; while * denotes significance at the 10% level, ** denotes significance at the 5% level and *** at the 1% level. All of the returns are monthly returns
Bold entries have significant values

constituents of major stock indices as their sample stocks. The positive autocorrelation effect might be stronger among large stocks than small and medium stocks in Australia; hence, large stocks are biased favorably toward finding momentum (Galariotis 2010). To mitigate this bias, we used a more random set of samples and did not focus on large stocks in particular. Our results show that the momentum strategy in Australia was somewhat similar to that in other developed markets in terms of economic profitability, evidenced by the returns generated by J3K3 (8.5% per annum), which fell within the range of 9%–18% per year in the US and other developed markets. In the unreported results for risk-adjusted returns, momentum profits remained robust. In fact, the economic significance of risk-adjusted returns was found to be slightly higher. This is consistent with Wang and Wu (2011) in that risk-adjusted returns tended to be higher than the average raw momentum returns due to the varying factor loadings in the time variation of momentum portfolios. The stylized facts are qualitatively similar with both measures of returns.

To explore the stability of the momentum effect in Australia, we also examined momentum strategies during several time periods: the crisis subperiods of the Asian financial crisis and the global financial crisis, as well as two noncrisis periods. Appendix contains the results: panel A shows the momentum returns during the 1997 Asian crisis subperiod, and panel B shows the returns of the 2007 global crisis subperiod. Panel C reports the results for the subperiod between the Asian crisis and the global crisis, and panel D contains those of the post-global crisis results.[1]

Industry momentum

The investigation of industry momentum in Australia used data for the same period—that is, September 1995 to September 2014. Table 2 shows the breakdown and summary statistics for each industry in the Australian market. An F-test was performed to test whether the cross-sectional mean returns of the industry groups were statistically different from each other, and the result was significant. This section analyzes the profitability and persistence of industry momentum strategies for the 16 industries. Table 3 shows the average returns of the winner and loser industries. Industry momentum returns correspond to the returns of the winner industry minus the loser industry (winner–loser).

As in evident in Table 3, the industry-level momentum effect was strong and persistent during the study period in the Australian equity market. The results show that all of the momentum strategies at the industry level yielded returns that were significantly

[1]In the Appendix, it can be seen in panel A that momentum returns are primarily positive, except for J9K9. Compared to the full sample period, there is no material difference in terms of the strength and persistence of the momentum effect during the Asian crisis subperiod. This is somewhat expected since the crisis only had a small effect on the Australian stock market. Next, turning to the global financial crisis, panel B shows that all of the strategies experienced momentum reversals. This can be taken to mean that momentum returns during the global crisis subperiod do provide some clues about the effect of economic downturn on momentum profitability. Our finding corroborates some other studies suggesting that the momentum effect is highly variable over time and sensitive to market states. The negative returns experienced during this subperiod occurred either because prior losers outperformed prior winners or because the negative returns caused by prior losers were less steep than the negative returns contributed by prior winners. Most of these returns, however, are not statistically distinguishable from zero and hence lack statistical reliance. We attribute this result to the relative resilience of Australia's financial system during the crisis period. The Australian equity market reportedly took longer to reflect the adverse outcomes of the subprime crisis in the early phase. Not only did stock prices (except bank-share prices) continue to rise six months after the first signs of the crisis but the financial system was also more resilient than that of many other countries. That said, the Australian stock market saw a large decline that caused a nearly 10% reduction in Australian household wealth by March 2009. Hence, while the results observed in panel B are believed to align with studies showing negative momentum during significant market downturns, the Australian effect is not extremely severe due to its resilient financial market. As a robustness check, we also performed momentum analyses over the subperiods that excluded the two crises. The results were similar qualitatively during the period between the Asian crisis and the global crisis and during the period after the global crisis. Interestingly, however, momentum returns appeared to be stronger economically after the global crisis. Stronger momentum returns were driven by the winner portfolios, as evidenced by the more significant positive returns that turned around after the global crisis. This corroborates Grinblatt and Han's (2005) underreaction model, which argues that winners exhibit greater momentum after a decreasing market. Our results are also consistent with Phua et al. (2010), who found that momentum returns are stronger during up market states.

Table 2 Summary Statistics of Industries (September 1995 to September 2014)

Industry name	Industry code	Number of firms	Percentage	Mean returns	Standard deviation
Oil & Gas	0500	84	11.0%	0.0156	0.2405
Chemicals	1300	11	1.4%	0.0094	0.1896
Basic Resources	1700	295	38.6%	0.0179	0.2936
Construction & Material	2300	31	4.1%	0.0123	0.1718
Industrial Goods & Services	2700	82	10.7%	0.0120	0.1922
Automobiles & Parts	3300	5	0.7%	0.0144	0.2120
Food & Beverage	3500	25	3.3%	0.0035	0.1289
Personal & Household Goods	3700	21	2.7%	0.0119	0.1872
Healthcare	4500	58	7.6%	0.0129	0.2649
Retail	5300	32	4.2%	0.0118	0.1158
Media	5500	22	2.9%	0.0094	0.2492
Travel & Leisure	5700	24	3.1%	0.0139	0.1903
Telecommunications	6500	10	1.3%	0.0122	0.1891
Utilities	7500	14	1.8%	0.0098	0.1612
Real Estate	8600	17	2.2%	0.0125	0.1488
Technology	9500	33	4.3%	0.0162	0.2741
Total		764	100%		
Average				0.0146 (0.0154)	
F-Statistic (all = 0)				2.09	
p-value				(0.0033)	

positive for all of the horizons. Among the 16 strategies, J3K3 and J9K3 yielded the highest positive returns—12.28% and 12.47% per annum, respectively. Overall, strategies that require a three-month holding period provided the strongest returns for any given value of J. Although stock-level momentum was found to be reasonably strong in Australia, trading strategies based on industry grouping offered better returns and more pronounced significance, except for J6K3. In addition, evidence of loser industries outperforming winner industries within the time horizons examined in this study was not found.

The results of this study are consistent with some prior Australian evidence. Li et al. (2014) documented the presence of industry momentum in Australia but found that significant and positive returns congregated only at longer ranking and holding horizons. In that study, the J9K3 strategy generated a significant yearly return of 11%. Economic profit was comparable to the 12.42% yearly return observed in the present study. On the contrary, Gupta et al. (2010) documented larger profits of 15%. This discrepancy may be attributable to different underlying sample pools. Li et al. (2014) utilized the constituents of the S&P/ASX200 index, covering a sample period from 2001 to 2010, while Gupta et al. (2010) utilized 135 stocks from 1993 to 2007. Our study, however, utilized more than 700 stocks spanning a broader horizon (1995–2014). Similar to stock-level momentum, Australian evidence for industry momentum was economically larger than evidence from other developed markets—namely, 5.5% for US stocks (Moskowitz and Grinblatt 1999; Swinkels 2002) and 7.83% for European stocks (Swinkels 2002; Ji and Giannikos 2010). Our findings thus provide an indication that in Australia, stocks in the same industry have

Table 3 Performance of Industry Momentum Trading Strategies (September 1995 to September 2014)

Strategy	Winner	Loser	Winner-Loser	
J3K3	0.0175	0.0078	**0.0097**	***
	5.97	*2.99*	*4.74*	
J3K6	0.0167	0.0095	**0.0073**	***
	7.71	*4.84*	*5.35*	
J3K9	0.0169	0.0099	**0.0071**	***
	8.55	*6.37*	*6.26*	
J3K12	0.0160	0.0103	**0.0057**	***
	9.86	*8.13*	*6.85*	
J6K3	0.0149	0.0093	**0.0056**	***
	5.17	*3.39*	*2.44*	
J6K6	0.0157	0.0099	**0.0059**	***
	6.52	*4.99*	*3.51*	
J6K9	0.0158	0.0100	**0.0059**	***
	7.50	6.42	4.61	
J6K12	0.0161	0.0106	**0.0055**	***
	8.79	*8.45*	*5.25*	
J9K3	0.0179	0.0081	**0.0098**	***
	5.94	*3.31*	*4.11*	
J9K6	0.0165	0.0091	**0.0075**	***
	6.85	*5.30*	*4.21*	
J9K9	0.0165	0.0099	**0.0067**	***
	7.81	*7.44*	*4.51*	
J9K12	0.0158	0.0108	**0.0050**	***
	8.60	*10.01*	*4.03*	
J12K3	0.0171	0.0081	**0.0090**	***
	5.59	*3.35*	*3.75*	
J12K6	0.0163	0.0094	**0.0070**	***
	6.38	*5.62*	*3.74*	
J12K9	0.0156	0.0108	**0.0048**	***
	6.98	*8.33*	*3.03*	
J12K12	0.0154	0.0117	**0.0037**	***
	8.15	*10.79*	*2.84*	

Sample industries were ranked by their past J-month returns. The top (bottom) 20% of performers were assigned to the winner (loser) industry portfolio. There was a one-month gap between the formation and investment periods. A long (short) position was then taken for the winner (loser) industry portfolio. Winner minus loser represents the momentum returns. All of the returns are on a monthly basis. The t-statistics are italicized; *** represents a 1% significance level
Bold entries have significant values

a strong tendency to move together, and the tendency is probably stronger in Australia compared to other developed markets.

Industry-neutral portfolios

In this section, we use an industry-dependent portfolio to examine whether industry influence can be a source of reward for stock momentum. To ensure a reasonably

Table 4 (Part I). Industry-Neutral Momentum Portfolios

Strategy	Panel A: Basic Resources				Panel B: Oil & Gas			
	Winner	Loser	Winner-Loser		Winner	Loser	Winner-Loser	
J3K3	0.0227	0.0177	0.0050		0.0124	0.0116	0.0008	
	4.47	*3.56*	*1.50*		*3.01*	*2.99*	*0.26*	
J3K6	0.0253	0.0234	0.0019		0.0153	0.0146	0.0006	
	6.23	*6.12*	*0.78*		*5.76*	*5.06*	*0.41*	
J3K9	0.0277	0.0261	0.0016		0.0155	0.0164	−0.0008	
	8.65	*7.61*	*0.87*		*7.80*	*6.86*	*−0.75*	
J3K12	0.0274	0.0254	0.0020		0.0158	0.0167	−0.0010	
	10.02	*8.44*	*1.46*		*8.96*	*8.40*	*−1.17*	
J6K3	0.0241	0.0215	0.0026		0.0113	0.0142	−0.0029	
	4.88	*3.94*	*0.67*		*2.81*	*3.38*	*−0.91*	
J6K6	0.0216	0.0259	−0.0043		0.0113	0.0169	**−0.0056**	***
	6.47	*6.10*	*−1.52*		*4.34*	*5.43*	*−2.80*	
J6K9	0.0235	0.0271	−0.0037		0.0135	0.0178	**−0.0043**	***
	8.55	*7.49*	*−1.58*		*6.70*	*6.85*	*−2.95*	
J6K12	0.0224	0.0286	**−0.0062**	***	0.0134	0.0180	**−0.0046**	***
	9.19	*8.93*	*−3.40*		*7.74*	*8.47*	*−4.05*	
J9K3	0.0211	0.0227	− 0.0016		0.0148	0.0168	−0.0019	
	4.47	*3.96*	*−0.38*		*3.74*	*3.68*	*−0.55*	
J9K6	0.0191	0.0256	**−0.0065**	**	0.0146	0.0174	−0.0028	
	5.90	*5.94*	*−2.07*		*5.53*	*5.34*	*−1.22*	
J9K9	0.0199	0.0273	**−0.0074**	***	0.0142	0.0186	**−0.0044**	***
	7.23	*7.61*	*−3.05*		*7.07*	*7.30*	*−2.68*	
J9K12	0.0188	0.0269	**−0.0081**	***	0.0130	0.0195	**−0.0065**	***
	7.58	*8.55*	*−4.12*		*7.43*	*9.62*	*−5.26*	
J12K3	0.0180	0.0190	−0.0010		0.0097	0.0143	−0.0045	
	3.84	*3.39*	*−0.23*		*2.39*	*3.42*	*−1.41*	
J12K6	0.0190	0.0264	**−0.0074**	**	0.0100	0.0178	**−0.0077**	***
	5.70	*5.95*	*−2.39*		*3.97*	*5.71*	*−3.60*	
J12K9	0.0174	0.0264	**−0.0090**	***	0.0093	0.0199	**−0.0106**	***
	6.27	*7.22*	*−3.62*		*4.43*	*8.04*	*−6.45*	
J12K12	0.0147	0.0266	**−0.0119**	***	0.0092	0.0198	**−0.0107**	***
	5.60	*8.47*	*−5.41*		*4.99*	*9.58*	*−8.53*	

In a given industry, stocks were sorted into quintiles based on past returns. Within each industry, the top 20% of performers were winners, and the bottom 20% were losers. After a one-month lag, a long position was taken as the winner and short as the loser. Momentum returns were calculated as winner returns minus loser returns. All of the returns are on a monthly basis. The t-statistics are italicized; ** represents significance at the 5% level and *** at the 1% level
Bold entries have significant values

sufficient size for each portfolio, we considered only the following four largest industries: basic resources (295 firms), oil and gas (84 firms), industrial goods and services (82 firms), and healthcare (58 firms). Tables 4 and 5 presents the returns of industry-neutral momentum portfolios.

Tables 4 and 5 shows the overall positive returns for the more recent ranking and investment horizons and some negative momentums for the more distant horizons. For example, in oil and gas, half of the strategies generated a negative momentum, of which

Table 5 (Part II). Industry-Neutral Momentum Portfolios

Strategy	Panel C: Industrial Goods & Services				Panel D: Health Care			
	Winner	Loser	Winner-Loser		Winner	Loser	Winner-Loser	
J3K3	0.0149	0.0052	**0.0097**	***	0.0269	0.0107	**0.0162**	***
	4.55	*1.49*	*3.40*		*6.32*	*2.45*	*4.06*	
J3K6	0.0165	0.0085	**0.0080**	***	0.0227	0.0163	**0.0064**	***
	6.71	*3.19*	*4.54*		*7.33*	*5.40*	*2.72*	
J3K9	0.0150	0.0079	**0.0071**	***	0.0203	0.0173	0.0030	
	7.73	*3.76*	*6.15*		*8.04*	*6.76*	*1.70*	
J3K12	0.0130	0.0103	**0.0027**	***	0.0175	0.0182	−0.0007	
	8.06	*5.78*	*3.44*		*8.16*	*7.81*	*−0.59*	
J6K3	0.0156	0.0084	**0.0072**	**	0.0246	0.0138	**0.0108**	**
	5.04	*2.33*	*2.28*		*5.98*	*2.87*	*2.38*	
J6K6	0.0151	0.0083	**0.0068**	***	0.0224	0.0167	0.0058	
	6.49	*3.20*	*3.71*		*7.01*	*4.97*	*1.84*	
J6K9	0.0127	0.0087	**0.0040**	***	0.0190	0.0174	0.0016	
	6.72	*4.14*	*3.19*		*7.30*	*6.15*	*0.75*	
J6K12	0.0109	0.0103	0.0007		0.0159	0.0193	**−0.0034**	**
	6.80	*6.06*	*0.67*		*7.47*	*8.22*	*−2.44*	
J9K3	0.0152	0.0083	0.0069		0.0232	0.0147	0.0085	
	4.86	*2.28*	*2.31*		*5.20*	*3.02*	*1.64*	
J9K6	0.0129	0.0104	0.0025		0.0173	0.0179	−0.0005	
	5.43	*3.85*	*1.21*		*5.59*	*4.96*	*−0.15*	
J9K9	0.0120	0.0104	0.0016		0.0153	0.0198	−0.0045	
	5.96	*4.88*	*0.98*		*5.87*	*6.97*	*−1.78*	
J9K12	0.0096	0.0123	−0.0026		0.0109	0.0222	**−0.0113**	***
	5.65	*6.94*	*−1.95*		*5.21*	*9.62*	*−6.59*	
J12K3	0.0089	0.0069	0.0020		0.0160	0.0145	0.0015	
	2.90	*1.87*	*0.69*		*4.29*	*3.01*	*0.31*	
J12K6	0.0100	0.0086	0.0013		0.0144	0.0182	−0.0038	
	4.17	*3.43*	*0.67*		*5.14*	*5.43*	*−1.24*	
J12K9	0.0090	0.0099	−0.0009		0.0098	0.0231	**−0.0133**	***
	4.27	*4.95*	*−0.58*		*4.79*	*8.36*	*−6.27*	
J12K12	0.0075	0.0122	**−0.0047**	***	0.0070	0.0224	**−0.0153**	***
	4.05	*7.27*	*−3.51*		*4.18*	*10.03*	*−9.80*	

In a given industry, stocks were sorted into quintiles based on past returns. Within each industry, the top 20% of performers were winners, and the bottom 20% were losers. After a one-month lag, a long position was taken as the winner and short as the loser. Momentum returns were calculated as winner returns minus loser returns. All of the returns are on a monthly basis. The t-statistics are italicized; ** represents significance at the 5% level and *** at the 1% level
Bold entries have significant values

eight were significantly negative. By contrast, healthcare generated more positive returns, but only three were significant. Industrial metals and mining produced mixed results, but the majority were insignificant. These results suggest that the industry aspect contributes to the profitability of momentum investment strategies. When momentum strategies were implemented within the same industry, the significant positive returns that were previously observed dissipated in three of the four industries. Specifically, industry-neutral portfolios produced a monthly mean return of – 0.25%, which was insignificant (t = – 0.61). In other words, the impressive profitability and strong significance observed in the previous analysis dissipated, or were even reversed, when the industry effect was accounted for.

In Australia, the momentum effect at the industry level was found to be stronger and more persistent than the momentum effect at the stock level. The results were consistent with the limited extant Australian evidence but economically larger than those for the US and Europe. Moskowitz and Grinblatt (1999) argued that industry momentum may be attributable to investor herding behavior. Herding behavior can explain why industry-specific news is not incorporated into stock prices instantaneously. Investors likely herd toward certain hot industries and sectors and flock out of other cold industries and sectors. The price pressure resulting from investor herding behavior therefore causes return persistence.

Liquidity-momentum profitability

Table 6 shows the descriptive statistics for five different levels of spread in the sample of Australian stocks. The total number of liquidity-month observations is 77,223. Consistent with prior evidence, smaller firms are less liquid (represented by larger spread) than larger firms. Moreover, a noticeable negative relationship exists between stock returns and spread. That is, stocks with higher liquidity are linked with higher past stock returns. This is consistent with the traditional liquidity hypothesis, which suggests that stocks with higher liquidity exhibit lower expected returns. Next, in Table 7 we show the performances of the liquidity-momentum portfolios by way of two-way sorting.

As indicated in Table 7, both the winner and loser portfolios of the smallest-spread stocks outperformed the winner and loser portfolios of the largest-spread stocks. Also, medium-high-liquidity stocks (L4) generated the highest momentum returns (1.48% per month or 19.34% per annum), followed by the medium-low group (L2). All of the momentum returns were significant except for the largest-spread (most illiquid) stocks. Although an increasing trend of momentum returns is observed when the spreads become narrower (more liquid), the pattern was not clear-cut. To investigate further, we compared the momentum returns of extreme-spread groups. First, we deducted the momentum return of L1 from that of L5, which yielded an insignificant positive return. When we compared the L4 and L1 momentum returns, we found a positive return of sizable magnitude and significance (1.09% per month or 13.87% per annum). Lastly, the excess of L4 over L2 was derived, but as with L5 – L1, although it yielded a positive return, it was not significant. In short, we did not find any strong statistical association

Table 6 Summary Statistics of Different Levels of Liquidity

	Spread		Average Size		Return	
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
Low liquidity/large spread (L1)	0.0976	0.0246	2.62	1.19	−0.0290	0.2227
Medium-low liquidity (L2)	0.0494	0.0121	3.43	1.38	−0.0019	0.2049
Medium liquidity (L3)	0.0286	0.0073	4.21	1.50	−0.0161	0.1915
Medium-high liquidity (L4)	0.0156	0.0049	5.28	1.57	0.0201	0.1654
High liquidity/small spread (L5)	0.0062	0.0042	6.88	1.71	0.0146	0.1300

Mean returns are on a monthly basis. Average size denotes market value—that is, share price multiplied by the number of ordinary shares in issue. Market value is displayed in a natural logarithm (ln) of millions of Australian dollars

Table 7 Returns of Liquidity-Momentum Portfolios

Level of Liquidity/Spread Size	Winner	Loser	Winner-Loser	
Low liquidity/large spread (L1)	−0.0244	−0.0284	0.0040	
	−7.95	*−8.83*	*1.63*	
Medium-low liquidity (L2)	−0.0165	−0.0286	**0.0121**	***
	−4.38	*−9.31*	*4.87*	
Medium liquidity (L3)	0.0005	−0.0104	**0.0109**	***
	0.12	*−2.87*	*4.24*	
Medium-high liquidity (L4)	0.0176	0.0028	**0.0148**	***
	4.92	*0.85*	*7.05*	
High liquidity/small spread (L5)	0.0202	0.0118	**0.0084**	***
	6.51	*4.33*	*4.01*	
High minus low (L5-L1)			0.0045	
			1.33	
Medium high minus low (L4-L1)			**0.0109**	***
			3.83	
Medium high minus medium low (L4-L2)			0.0027	
			1.00	

The strategy of J3K3 was used. Sample stocks were first segregated into five levels of bid-ask spread. L1 denotes the largest spread/lowest liquidity, and L5 denotes the smallest spread/highest liquidity. Winner minus loser denotes momentum returns. High minus low (L5-L1) was calculated as the returns of the high liquidity group minus the returns of the low liquidity group. The t-statistics are italicized and measure the significance levels of the returns; ** (***) represents the 5% (1%) significance level. All of the returns were on a monthly basis
Bold entries have significant values

between liquidity measured by bid-ask spread and momentum profits except that the momentum strategy did not seem to work in the most illiquid stocks (L1), an observation that is difficult to reconcile with the liquidity explanation. Our results are not dissimilar to those of Demir et al. (2004). That study tested the strategies on Australian index stocks and found that a momentum strategy implemented on illiquid stocks yielded lower or even negative returns, and overall liquidity differences did not explain the momentum effect. Thus, we take our results to mean that the liquidity factor does not explain the observed profits in momentum strategies in Australia. As a robustness check, we also proxied liquidity using trading volume. The results were quantitatively similar and hence not reported here.

Conclusion

This study adds to the momentum literature on Australia, given the limited and contradictory evidence for that market. We found that an active investment strategy based on the principle of return continuation can be profitable in the Australian stock market. The momentum effect was found to be a stable occurrence across various time periods, except the period of global financial crisis. We further noted that momentum returns were of greater economic significance after the global crisis, and excess returns were driven mainly by winner portfolios. This corroborates Grinblatt and Han's (2005) underreaction theory in which winners exhibit greater momentum after a decreasing market. Next, this study found evidence that investors can capture the momentum effect by constructing industry portfolios in a concerted way. We found that industries that perform well continue to outperform other industries, and vice versa. This suggests

Appendix

Table 8 Momentum Returns Across Different Time Periods

Panel A: Asian Financial Crisis (January 1997 to December 1999)					Panel B: Global Financial Crisis (January 2007 to December 2009)			
Strategy	Winner	Loser	Winner-Loser		Winner	Loser	Winner-Loser	
J3K3	0.0177	0.0096	0.0081		0.0076	0.0129	−0.0054	
	2.25	*1.03*	*1.90*		*0.48*	*0.91*	*−1.02*	
J3K6	0.0181	0.0086	**0.0095**	***	−0.0085	0.0013	−0.0098	
	2.12	*1.07*	*5.38*		*−0.75*	*0.09*	*−1.56*	
J3K9	0.0143	0.0067	**0.0075**	***	−0.0213	−0.0153	− 0.0060	
	1.86	*0.94*	*7.52*		*−3.51*	*−1.52*	*−1.10*	
J6K3	0.0177	0.0096	**0.0128**	***	0.0036	0.0173	−0.0138	
	2.25	*1.03*	*3.10*		*0.26*	*1.06*	*−1.69*	
J6K6	0.0204	0.0073	**0.0131**	***	−0.0099	0.0042	−0.0141	
	2.19	*0.99*	*5.44*		*−1.02*	*0.27*	*− 1.78*	
J6K9	0.0110	0.0070	**0.0039**	***	−0.0206	−0.0158	−0.0047	
	1.38	*1.11*	*2.22*		*−3.28*	*−1.58*	*−0.90*	
J9K3	0.0221	0.0132	0.0133		0.0038	0.0219	**−0.0181**	**
	2.45	*3.72*	*1.90*		*0.29*	*1.29*	*−2.06*	
J9K6	0.0160	0.0119	0.0041		−0.0083	0.0130	−0.0130	
	1.74	*1.70*	*1.59*		*−0.82*	*3.35*	*−1.53*	
J9K9	0.0081	0.0106	−0.0025		−0.0210	−0.0143	− 0.0068	
	1.06	*1.64*	*−1.85*		*−3.46*	*−1.47*	*− 1.18*	
Panel C (January 2000 to December 2006)					Panel D (January 2010 to September 2014)			
Strategy	Winner	Loser	Winner-Loser		Winner	Loser	Winner-Loser	
J3K3	0.0191	0.0112	**0.0079**	***	0.0094	−0.0012	**0.0106**	***
	4.84	*2.56*	*3.89*		*1.42*	*−0.17*	*4.90*	
J3K6	0.0190	0.0143	**0.0046**	***	0.0085	−0.0004	**0.0089**	***
	6.56	*4.13*	*3.09*		*1.77*	*−0.08*	*13.55*	
J3K9	0.0199	0.0162	**0.0037**	***	0.0040	−0.0051	**0.0091**	***
	8.74	*5.71*	*3.14*		*1.32*	*−1.78*	*11.14*	
J6K3	0.0176	0.0120	**0.0056**	**	0.0102	−0.0010	**0.0111**	***
	4.63	*2.58*	*2.23*		*1.51*	*−0.14*	*6.90*	
J6K6	0.0176	0.0144	0.0033		0.0092	0.0004	**0.0088**	***
	6.39	*3.97*	*1.77*		*1.90*	*0.09*	*8.54*	
J6K9	0.0180	0.0161	0.0019		0.0029	−0.0044	**0.0073**	***
	8.04	*5.59*	*1.38*		*0.94*	*−1.60*	*8.77*	
J9K3	0.0171	0.0125	0.0046		0.0111	−0.0031	**0.0142**	***
	4.46	*2.64*	*1.80*		*1.69*	*−0.49*	*6.93*	
J9K6	0.0166	0.0146	0.0020		0.0088	−0.0008	**0.0096**	***
	5.97	*4.06*	*1.04*		*1.80*	*−0.18*	*6.86*	
J9K9	0.0164	0.0166	−0.0002		0.0017	−0.0037	**0.0054**	***
	7.41	*5.86*	*−0.14*		*0.53*	*−1.47*	4.25	

This table reports mean returns on a monthly basis. Sample stocks are sorted by the 20% breakpoint. The t-statistics are italicized; ** denotes significance at the 5% level and *** at the 1% level. We did not perform strategies with formation and holding periods of 12 months due to the relatively brief period of analysis

Bold entries have significant values

the exploitability of return continuation and profit-making opportunities for traders at the industry level. For example, traders can segment stocks based on industries and apply the strategy of buying the constituent stocks of top-performing industries while selling the stocks of the worst-performing industries. This finding demonstrates the importance and relevance of the industry in explaining the return-generation process, and it lends support to the notion that the industry component should be incorporated in pricing equities. More interestingly, we found that momentum strategies at the industry level perform better than stock-level momentum strategies, implying a potentially more profitable avenue for active investment management. Finally, we investigated whether the momentum effect can be explained by the liquidity effect. Our results indicated that the liquidity effect does not subsume the momentum effect. Based on our results, we conclude that the momentum effect is not explainable by the liquidity factor. Put differently, the results do not validate our initial conjecture that liquidity would have clear predictive power for momentum profitability.

Future research can consider various other criteria to classify stocks. Potential interdisciplinary studies could combine momentum studies with classification algorithms, which is an increasingly important research area. As pointed out by Kao et al. (2019), big data development has opened up new avenues for future theoretical and applied research. Thus, combining the two research domains could potentially be a viable direction for future research.

Acknowledgements
Not applicable.

Authors' contributions
TYM performed the examinations and analysis of momentum studies, and was the main contributor in writing the manuscript. CFF involved in the data interpretation part. Both authors read and approved the final manuscript.

Funding
This research is supported by Xiamen University Malaysia Research Fund (Grant No: XMUMRF/2019-C3/ISEM/0016).

Availability of data and materials
The dataset analyzed during the current study are available from the corresponding author upon reasonable request.

Competing interests
The authors declare that they have no competing interests.

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Received: 30 January 2019 Accepted: 15 October 2019
Published online: 02 December 2019

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