Pacific-Basin Finance Journal 59 (2020) 101258

Contents lists available at ScienceDirect

Pacific-Basin Finance Journal

journal homepage: www.elsevier.com/locate/pacfin

Enhancing momentum profits in the Taiwan Stock Market: The role of extreme absolute strength

Chaonan Lin[a], Chuanxin Xia[b], Nien-Tzu Yang[c,*], Sheng-Yung Yang[d]

[a] School of Management, Xiamen University, Xiamen, China
[b] Guanghua School of Management, Peking University, Peking, China
[c] Department of Business Management, National United University, Miaoli, Taiwan
[d] Department of Finance, National Chung Hsing University, Taichung, Taiwan

ARTICLE INFO

JEL Classification:
G11
G12
G14

Keywords:
Momentum
Absolute strength
Extreme past returns
Taiwan Stock Market

ABSTRACT

We show that stocks with extreme absolute strength are highly volatile and thus attenuate the profitability of momentum in Taiwan, a market that has been widely documented as an exception of the momentum phenomenon. An enhanced momentum strategy that removes these stocks from the winner and loser portfolios generates significant profitability in the intermediate term. A major advantage of the enhanced momentum strategy is its robust profitability over time. More importantly, it is free from the momentum crashes. We provide further evidence to show that return dispersion and information uncertainty are closely related to momentum profitability in the cross-section when stocks with extreme absolute strength are removed.

1. Introduction

Starting from the publication of Jegadeesh and Titman (1993), understanding the nature of intermediate-term momentum has become an important issue to both academic researchers and practitioners. Despite its soundness in major stock markets, the absence of the momentum phenomenon in the Taiwan stock market has been documented as a remarkable exception (Hameed and Kusnadi, 2002; Chui et al., 2003, 2010; Du et al., 2009; Lin et al., 2016; Yang et al., 2018).

Among the vast literature on the sources of momentum, two lines of research have proposed distinct explanations for momentum based on extreme past performances of stocks. Bandarchuk and Hilscher (2013) show that momentum profits can be enhanced by trading in stocks with extreme past returns. Once this effect is controlled, the explanatory power of several firm characteristics disappears almost entirely. Yang and Zhang (2019), in contrast, propose that stocks with extreme absolute strength, i.e. those experienced substantial positive or negative returns recently,[1] have extraordinarily high volatility and thus lose their momentum. Removing these stocks from the winner and loser portfolios of Jegadeesh and Titman's (1993) price momentum strategy is able to enhance momentum profitability.

While the two competing explanations have been examined exclusively for the U.S. stock markets, whether they are applicable to other markets and in particular, those that exhibit no momentum phenomenon, still remains unexamined in the literature. As the Taiwan stock market is a remarkable exception of momentum, we propose two research questions to address this issue: (i) whether

* Corresponding author at: 1, Lienda, Miaoli 36003, Taiwan
E-mail address: nanzy@nuu.edu.tw (N.-T. Yang).

[1] The concept of absolute strength is initiated by Gulen and Petkova (2018), who propose that the past performance of a stock should be evaluated compared with the entire historical distribution of returns rather than just compared with contemporary benchmark returns in the cross-section.

https://doi.org/10.1016/j.pacfin.2019.101258
Received 18 July 2019; Received in revised form 1 November 2019; Accepted 1 December 2019
Available online 07 December 2019
0927-538X/

the absence of momentum in Taiwan is attributed to extreme past performances of stocks, and (ii) whether we can take advantage of extreme past performances to develop a trading strategy that is able to enhance the momentum profitability.

We take a first glance at the average monthly returns over past 12 month and the averaged standard deviations against the percentiles of stock-level past returns calculated from month t - 12 to month $t - 1$.[2] The red dots in Fig. 1 represent the average past returns across percentiles, with scale marked on the right vertical axis. Over our sample period from January 1990 to December 2018,[3] the average past performances range from −17.793% for the 1st percentile to 41.860% for the 99th percentile per month. We also plot the average standard deviations in light grey line segments with corresponding scale marked on the left vertical axis. We observe that the average standard deviations display a U-shaped relation with past performance, with stocks experienced extreme past performance, i.e., those ranked at the highest and lowest percentiles, having extremely high return standard deviations.

Over the same period, the price momentum strategy of Jegadeesh and Titman (1993) generates an insignificant return of −0.158% per month in the Taiwan stock market when the holding period is set to be six months. While it is yet clear whether the absence of the momentum phenomenon is attributed to the extremely volatile stocks of winner and loser portfolios, Yang and Zhang (2019) have demonstrated that extremely high absolute strength actually induces volatilities in future profitability of stocks. Removing these stocks could generate more stable profitability for momentum strategies. Taking advantage of Yang and Zhang's (2019) observation based on the U.S. markets, we propose that the high volatility of stocks with extreme relative strength as shown in Fig. 1 might be concentrated in stocks with extreme absolute strength. Indeed, as we show in the blue dots of Fig. 1, the return standard deviations have been reduced by a fair amount when we exclude stocks with absolute strength ranked at the top (mostly belonging to winners) and bottom (mostly belonging to losers) 3% of the historical distribution.

Removing stocks with extreme absolute strength is beneficial not only to avoid volatile stocks but also to enhance momentum profitability in the Taiwan stock market. An enhanced momentum strategy that removes stocks with absolute strength ranked at the top 3% from the winner portfolio and those ranked at the bottom 3% from the loser portfolio generates a significant average return of 1.349% per month, which is a substantial improvement on the standard price momentum. When we remove a larger amount of stocks, for example, 4% or 5% of stocks with extreme absolute strength, the momentum profits can be further enhanced.

The traditional price momentum in Taiwan, despite its overall unprofitability, is prone to substantial losses when the market reverses (Asem and Tian, 2010), when market volatility is high (Wang and Xu, 2015), and during crash periods (Daniel and Moskowitz, 2016).[4] The enhanced momentum that removes stocks with extreme absolute strength, in contrast, shows robust profitability over time as these time-varying predictors all fail to account for the performance of the enhanced momentum. This observation is consistent with the U.S. evidence of Yang and Zhang (2019) that the removal of extreme absolute strength effectively alleviates the problem of momentum crashes, and thus highlights the advantage of the enhanced momentum in an out-of-sample outside the U.S. markets.

We next explore whether the cross-sectional variants are responsible for the momentum profitability in Taiwan. Following Bandarchuk and Hilscher (2013), we consider two measures of volatility in past returns (including idiosyncratic volatility and momentum strength) and nine characteristics at the firm level. By forming quintile portfolios based on each measure, we find that none of the variables generates significant variations in producing differences in momentum profits. Once the stocks with extreme absolute strength are removed, we find that measures associated with volatility and information uncertainty (including firm age and analyst coverage) are positively related to momentum profits with statistical significance.

To further compare the relative explanatory ability between volatility and firm characteristics on the enhanced momentum profits, we perform cross-sectional regressions of characteristics on volatility, and the other way around, to obtain residual characteristics or residual volatility measures. We then form enhanced momentum profits separately for each residual characteristic (volatility) quintile to control for the effect of volatility (characteristic), and we find that idiosyncratic volatility and firm age retain the most robust explanatory ability for the enhanced momentum profitability that is independent of other effects.

This study makes at least three contributions to the literature. First, we show that stocks with extreme past performance tend to have extremely high volatilities. This phenomenon has important implications to the absence of momentum in the Taiwan stock market. Second, the removal of stocks with extreme absolute strength could attenuate the extreme volatilities of momentum components and further results in significant momentum profitability that is robust over time. This observation is an important extension of Yang and Zhang (2019) as it shows that the enhanced momentum strategy could be effective even in a market without the existence of the momentum phenomenon. Finally, we show that the removal of stocks with extreme absolute strength could also change the relation between momentum and cross-sectional attributes. Unlike Bandarchuk and Hilscher's (2013) evidence that return volatility is the main determinant of momentum in the U.S. markets, we show that information uncertainty and volatility both play important roles for momentum in Taiwan conditional on the removal of stocks with extreme absolute strength. This is an important extension of Bandarchuk and Hilscher (2013) as whether the removal of extreme stocks could change the relation between momentum profitability and firm-level characteristics has yet been explored in the literature.

The rest of the paper is organized as follows. Section 2 describes the data and the construction of momentum strategies based on

[2] The standard deviations are calculated using weekly return data over past 12 months ending in month $t - 1$.

[3] The sample period starts from January 1990 because we require sufficient observations in the time series to develop the historical benchmark distribution of returns in measuring absolute strength of stocks. We thus use the return data back to January 1971 to determine the breakpoints of absolute strength and use the post-1990 period as the main analyses.

[4] Daniel and Moskowitz (2016) observe infrequent and persistent strings of negative momentum returns for periods following market declines, when market volatility is high, and are contemporaneous with market rebounds, which they refer to as the momentum crashes.

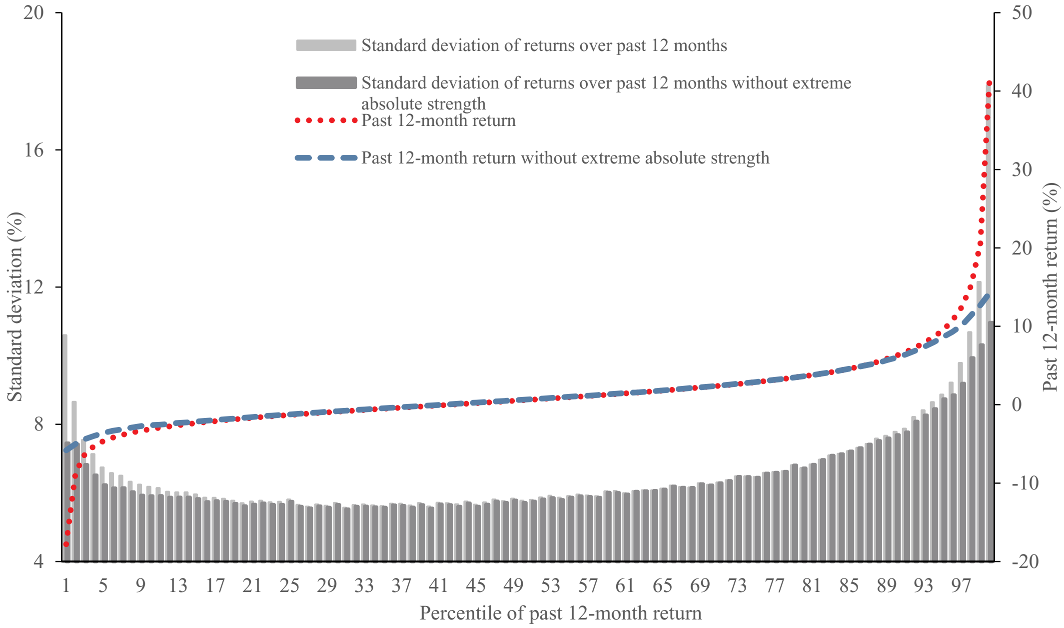

Fig. 1. Relative strength and past performance

past returns and absolute strength. We next investigate the impacts of extreme absolute strength on momentum profitability and propose the enhanced momentum strategy accordingly. We also verify the robustness and time-series patterns of the enhanced momentum. These analyses are presented in Section 3. Section 4 examines the impacts of extreme absolute strength on the cross-sectional attributes of momentum, and the last section concludes.

2. Data and the constructions of momentum strategies

To measure proxies of momentum, we use all common stocks listed on the Taiwan Stock Exchange (TSE), including OTC stocks, for the sample period from January 1971 to December 2018. We obtain necessary data from a local data vendor in Taiwan, namely the Taiwan Economic Journal (TEJ). Because we require the historical distribution of past returns to determine the breakpoints of absolute strength, our analyses are implemented mainly based on the period from January 1990 to December 2018, with the period from January 1971 to December 1989 used to construct the initial breakpoints. Our final sample consists of 32 firms in January 1971, 177 firms in January 1990, and 1,709 firms in December 2018, with an average of 978 firms per month for the 1990–2018 period.

We begin by measuring past performances of individual stocks. Following Jegadeesh and Titman (1993) and most literature of momentum, we focus mainly on the formation period of 12 month. That is, for each month *t*, we calculate the cumulative returns for all stocks from month *t* - 12 to month *t* - 1, denoted as PR12. We then sort individual stocks into decile portfolios according to their values of PR12 and allocate stocks belonging to the top (bottom) decile into the winner (loser) portfolio. The winner and loser portfolios are held with equal weights for the subsequent 1, 6, and 12 months starting from month *t*, with the 6- and 12-month holding periods involving an overlapping procedure as suggested by Jegadeesh and Titman (1993).[5,6] The JT momentum profit in a given month *t* is defined as the return difference between winner and loser portfolios in month *t*.

We next follow Gulen and Petkova (2018) and Yang and Zhang (2019) by using the historical distribution of PR12 over time and across stocks to identify the absolute strength of stocks. For a given calendar month in a year *y*, we calculate PR12 of all stocks in the same calendar month for every year prior to year *y*. We rank individual stocks' PR12 in this month based on this entire distribution. If a stock's PR12 is ranked at the top (bottom) *n*% of this distribution, we define it as an absolute strength winner (loser). This procedure is repeated for every calendar month across the period from January 1990 to December 2018. Although the ranking period starts from January 1999, we use return data back to January 1971 to ensure sufficient numbers of observations to establish the historical distribution. Similar to the JT momentum strategy, we identify stocks with PR12 ranked at the top (bottom) 10% of the historical

[5] Unlike most of the U.S. studies that require a 1-month skip between formation and holding periods, we do not impose this criterion because Taiwan stock market has been documented to exhibit positive autocorrelations in the short term because of the imposition of price limits (Yang et al., 2018). The results with the 1-month skip are virtually the same as presented in Table 3.

[6] We consider 6- and 12- month holding periods because they are widely examined since the publication of Jegadeesh and Titman (1993). The 1-month holding period becomes more popular in recent studies, especially for those that focus on higher moments, time-varying patterns, and crash risks of momentum (Barroso and Santa-Clara, 2015; Wang and Xu, 2015; Daniel and Moskowitz, 2016). We thus include the three sets of holding lengths to ensure the robustness of our results.

Table 1
Momentum profits.

	Full sample			January months			Non-January months		
	$K = 1$	$K = 6$	$K = 12$	$K = 1$	$K = 6$	$K = 12$	$K = 1$	$K = 6$	$K = 12$
Panel A: Profits to the JT momentum									
Winner	1.031	0.521	0.366	3.927	3.304	3.233	0.767	0.269	0.105
	(1.60)	(0.86)	(0.62)	(1.44)	(1.25)	(1.24)	(1.16)	(0.42)	(0.17)
Loser	0.816	0.679	0.796	6.361*	6.568*	6.485**	0.311	0.144	0.278
	(1.12)	(1.02)	(1.21)	(1.79)	(1.99)	(2.09)	(0.42)	(0.21)	(0.42)
WML	0.215	−0.158	−0.430	−2.434	−3.264*	−3.252**	0.456	0.125	−0.173
	(0.47)	(−0.43)	(−1.35)	(−0.96)	(−1.72)	(−2.06)	(0.95)	(0.32)	(−0.53)
FF3 alpha	0.342	−0.055	−0.330	−1.770	−2.426	−2.193	0.505	0.155	−0.141
	(0.83)	(−0.17)	(−1.20)	(−1.01)	(−1.56)	(−1.55)	(1.19)	(0.46)	(−0.51)
FF5 alpha	0.043	−0.328	−0.546**	−1.274	−2.578	−2.477	0.198	−0.129	−0.363
	(0.10)	(−1.04)	(−2.03)	(−0.72)	(−1.53)	(−1.64)	(0.46)	(−0.38)	(−1.32)
Panel B: Profits to the absolute strength momentum									
Winner	0.611	0.619	0.446	2.964	4.290*	4.772*	0.403	0.301	0.080
	(0.99)	(1.18)	(0.84)	(1.21)	(1.79)	(1.84)	(0.64)	(0.57)	(0.15)
Loser	0.802	0.924	0.897	4.636	5.779*	5.062*	0.463	0.504	0.545
	(1.37)	(1.61)	(1.58)	(1.47)	(1.88)	(1.76)	(0.77)	(0.89)	(0.97)
WML	−0.191	−0.305	−0.451	−1.672	−1.489	−0.290	−0.060	−0.203	−0.465
	(−0.34)	(−0.74)	(−1.12)	(−0.59)	(−0.79)	(−0.22)	(−0.10)	(−0.47)	(−1.08)
FF3 alpha	0.132	−0.001	−0.188	−1.375	−0.762	−0.505	0.205	0.038	−0.218
	(0.26)	(0.00)	(−0.53)	(−0.70)	(−0.64)	(−0.49)	(0.39)	(0.10)	(−0.60)
FF5 alpha	−0.112	−0.151	−0.288	−0.435	−0.355	−0.954	0.026	−0.079	−0.284
	(−0.20)	(−0.40)	(−0.76)	(−0.31)	(−0.40)	(−1.30)	(0.04)	(−0.20)	(−0.75)

This table reports the momentum profits for the sample period from January 1990 to December 2018. For each month *t*, we calculate the cumulative returns (PR12) for all stocks from month $t-12$ to month $t-1$. We then sort individual stocks into decile portfolios according to their values of PR12 and allocate stocks belonging to the top (bottom) decile into the winner (loser) portfolio. The winner and loser portfolios are held with equal weights for the subsequent 1, 6, and 12 months starting from month *t*. The JT momentum profit is calculated as the return difference between winner and loser portfolios. Panel A reports the average momentum profits for the full, January-only, and non-January subsamples, respectively. In addition, we calculate PR12 of all stocks in the same calendar month for every year prior to the current year. We rank individual stocks' PR12 in this month based on this entire distribution. If a stock's PR12 is ranked at the top (bottom) 10% of this distribution, we define it as an absolute strength winner (loser). We construct absolute momentum profits in the same way we construct the JT momentum and report the results in Panel B. Numbers in the parentheses are the *t*-statistics calculated using Newey and West's (1987) robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

distribution as absolute strength winners (losers) and construct the absolute strength momentum accordingly with 1-, 6-, and 12-month holding periods.

In Table 1, we report the momentum profits for JT and absolute strength momentum strategies, respectively. In addition to the full period from January 1990 to December 2018, we also provide the results for January-only and non-January months. To obtain abnormal returns for the strategies, we use Fama and French's (1993, 2015) three- and five-factor models as risk adjustments. The data on the factors are also obtained from TEJ, and they are constructed based on Fama and French's (1993, 2015) procedures. Consistent with prior studies, we show in Panel A that the JT momentum in Taiwan does not generate significant profits in the full sample period and non-January months. It also suffers from substantial losses in January months. This observation does not change as the length of holding period changes.

What surprises us is that absolute strength momentum is not profitable in Taiwan, as shown in Panel B. For the full period, it generates negative while insignificant profits. Although Gulen and Petkova (2018) have demonstrated that absolute strength momentum works well in the U.S. markets as well as four international markets, U.K., continental Europe, Japan, and Canada, our evidence suggests that the Taiwan market is an exception of this phenomenon. Absolute momentum differs from JT momentum in that it is less prone to reversals in January months. Its profits in January and non-January subsamples are both insignificant for all holding lengths. We also observe that the two strategies share one common feature that the lack of momentum profits for both strategies does not change when the two Fama-French factor models are used for risk adjustments.

3. Extreme absolute strength and momentum

So far we have verified that JT and absolute momentum strategies both fail to generate significant profits in Taiwan, and that extreme absolute strength seems to be responsible for the high volatility of stocks with extreme past performances. The next question we address in this section is whether extreme past performance accounts for the absence of momentum in Taiwan. In particular, we expect that the removal of such stocks, as advocated by Yang and Zhang (2019), could enhance momentum profitability in this market.

Table 2
Momentum profits excluding extreme absolute strength or extreme relative strength.

	K = 1					K = 6					K = 12				
	Winner	Loser	WML	FF3 alpha	FF5 alpha	Winner	Loser	WML	FF3 alpha	FF5 alpha	Winner	Loser	WML	FF3 alpha	FF5 alpha
Panel A: Profits to the JT momentum without extreme absolute strength															
1%	1.181**	0.840	0.341	0.352	0.265	1.142**	0.777	0.365	0.349	0.216	1.081*	0.861	0.220	0.197	0.086
	(2.11)	(1.45)	(1.21)	(1.36)	(0.99)	(2.05)	(1.39)	(1.32)	(1.42)	(0.89)	(1.95)	(1.56)	(0.83)	(0.86)	(0.37)
2%	1.255**	0.528	0.728*	0.652*	0.634*	1.386**	0.684	0.702*	0.673*	0.689	1.254**	0.781	0.473	0.460	0.564
	(2.23)	(0.90)	(1.84)	(1.95)	(1.77)	(2.58)	(1.23)	(1.70)	(1.68)	(1.58)	(2.48)	(1.45)	(1.22)	(1.14)	(1.24)
3%	1.668***	0.646	1.023*	1.029**	1.114*	1.787***	0.438	1.349**	1.225**	1.362*	1.743***	0.716	1.028*	0.857	0.995
	(3.19)	(1.10)	(1.93)	(1.99)	(1.74)	(3.34)	(0.88)	(2.53)	(2.25)	(1.88)	(3.27)	(1.43)	(1.80)	(1.48)	(1.31)
4%	1.507***	0.724	0.782**	0.624**	0.438	1.562***	0.337	1.225***	0.891**	0.699**	1.550***	0.509	1.040**	0.660*	0.526
	(3.08)	(1.49)	(2.21)	(2.24)	(1.63)	(3.21)	(0.70)	(2.70)	(2.52)	(1.98)	(3.20)	(1.04)	(2.11)	(1.71)	(1.30)
5%	1.567***	0.667	0.899***	0.784***	0.622**	1.706***	0.190	1.516***	1.210***	1.186***	1.670***	0.235	1.435***	1.107**	1.122**
	(3.23)	(1.38)	(2.64)	(2.87)	(2.32)	(3.55)	(0.41)	(3.22)	(3.28)	(3.04)	(3.53)	(0.50)	(2.70)	(2.55)	(2.41)
Panel B: Profits to the JT momentum without extreme relative strength															
1%	1.009*	0.927	0.082	0.099	0.032	1.008*	0.912	0.097	0.108	0.021	0.962*	0.918	0.044	0.057	0.001
	(1.77)	(1.59)	(0.38)	(0.49)	(0.16)	(1.78)	(1.61)	(0.61)	(0.71)	(0.15)	(1.71)	(1.64)	(0.35)	(0.47)	(0.01)
2%	0.974*	0.868	0.106	0.130	0.051	0.998*	0.867	0.131	0.143	0.050	0.943*	0.895	0.047	0.060	−0.001
	(1.72)	(1.48)	(0.48)	(0.62)	(0.24)	(1.76)	(1.54)	(0.81)	(0.92)	(0.34)	(1.67)	(1.61)	(0.37)	(0.49)	(−0.01)
3%	0.988*	0.863	0.124	0.137	0.058	1.016*	0.868	0.147	0.155	0.059	0.943*	0.894	0.049	0.061	0.000
	(1.74)	(1.46)	(0.55)	(0.64)	(0.27)	(1.79)	(1.53)	(0.90)	(0.98)	(0.39)	(1.67)	(1.60)	(0.39)	(0.49)	(0.00)
4%	0.928	0.837	0.091	0.097	0.023	0.989*	0.840	0.149	0.158	0.052	0.923	0.878	0.045	0.060	−0.005
	(1.61)	(1.40)	(0.37)	(0.41)	(0.10)	(1.75)	(1.48)	(0.89)	(0.98)	(0.34)	(1.64)	(1.57)	(0.35)	(0.47)	(−0.04)
5%	0.926	0.839	0.087	0.103	0.049	0.999*	0.815	0.184	0.198	0.083	0.938*	0.864	0.074	0.091	0.015
	(1.61)	(1.41)	(0.32)	(0.40)	(0.19)	(1.77)	(1.44)	(1.08)	(1.22)	(0.55)	(1.66)	(1.55)	(0.55)	(0.71)	(0.12)
Panel C: Profits to the absolute strength momentum without extreme absolute strength															
1%	1.122*	1.179*	−0.057	−0.017	−0.031	0.966*	1.111**	−0.145	−0.130	−0.200	0.963*	1.107**	−0.145	−0.159	−0.249
	(1.89)	(1.92)	(−0.20)	(−0.06)	(−0.11)	(1.68)	(1.99)	(−0.59)	(−0.56)	(−0.82)	(1.68)	(2.09)	(−0.54)	(−0.63)	(−0.92)
2%	0.953	0.955	−0.001	0.027	0.034	0.907	1.084*	−0.177	−0.163	−0.215	0.906	1.019*	−0.113	−0.129	−0.206
	(1.58)	(1.56)	(−0.01)	(0.10)	(0.12)	(1.57)	(1.94)	(−0.67)	(−0.65)	(−0.82)	(1.58)	(1.93)	(−0.41)	(−0.51)	(−0.75)
3%	0.944	0.972	−0.029	−0.005	−0.021	0.891	1.087*	−0.197	−0.186	−0.248	0.906	1.049**	−0.143	−0.157	−0.210
	(1.53)	(1.61)	(−0.10)	(−0.02)	(−0.07)	(1.53)	(1.95)	(−0.71)	(−0.71)	(−0.90)	(1.57)	(1.97)	(−0.49)	(−0.59)	(−0.75)
4%	0.949	0.965	−0.016	0.005	−0.012	0.849	1.132**	−0.282	−0.274	−0.338	0.914	1.073**	−0.159	−0.173	−0.233
	(1.56)	(1.58)	(−0.05)	(0.02)	(−0.04)	(1.44)	(2.03)	(−0.98)	(−1.01)	(−1.18)	(1.57)	(2.02)	(−0.55)	(−0.65)	(−0.82)
5%	0.971	0.998	−0.027	0.006	−0.023	0.879	1.070*	−0.191	−0.169	−0.223	0.904	0.967*	−0.063	−0.057	−0.134
	(1.58)	(1.62)	(−0.08)	(0.02)	(−0.07)	(1.46)	(1.88)	(−0.67)	(−0.62)	(−0.78)	(1.51)	(1.79)	(−0.22)	(−0.21)	(−0.47)

(continued on next page)

Table 2 (*continued*)

	K = 1					K = 6					K = 12				
	Winner	Loser	WML	FF3 alpha	FF5 alpha	Winner	Loser	WML	FF3 alpha	FF5 alpha	Winner	Loser	WML	FF3 alpha	FF5 alpha
Panel D: Profits to the absolute strength momentum without extreme relative strength															
1%	0.965	0.736	0.229	0.241	0.160	0.956	1.111**	−0.155	−0.165	−0.212	0.858	1.066**	−0.208	−0.203	−0.298
	(1.63)	(1.26)	(1.03)	(1.13)	(0.75)	(1.60)	(1.99)	(−0.79)	(−0.86)	(−1.06)	(1.47)	(1.98)	(−0.88)	(−0.89)	(−1.21)
2%	0.895	1.148**	−0.254	−0.259	−0.306	0.612	1.349**	−0.736**	−0.787**	−0.901**	0.576	1.372***	−0.796*	−0.859**	−1.017**
	(1.50)	(1.97)	(−0.87)	(−0.88)	(−0.98)	(1.06)	(2.52)	(−2.19)	(−2.30)	(−2.42)	(0.99)	(2.71)	(−1.92)	(−2.10)	(−2.30)
3%	0.808	1.070*	−0.262	−0.267	−0.365	0.526	1.323**	−0.797**	−0.807**	−1.030**	0.384	1.478***	−1.094**	−1.085**	−1.356**
	(1.24)	(1.83)	(−0.65)	(−0.67)	(−0.93)	(0.88)	(2.49)	(−2.04)	(−2.06)	(−2.42)	(0.65)	(2.88)	(−2.23)	(−2.22)	(−2.57)
4%	−0.260	1.235*	−1.496***	−1.539***	−1.618***	−0.049	1.391**	−1.440***	−1.459***	−1.601***	−0.157	1.576***	−1.733***	−1.730***	−1.862***
	(−0.40)	(1.90)	(−3.44)	(−3.42)	(−3.37)	(−0.08)	(2.43)	(−2.71)	(−2.71)	(−2.87)	(−0.26)	(2.86)	(−2.88)	(−2.84)	(−3.06)
5%	−0.096	1.614**	−1.711***	−1.649***	−1.700***	−0.211	1.636***	−1.848***	−1.820***	−1.946***	−0.277	1.943***	−2.221***	−2.202***	−2.348***
	(−0.15)	(2.43)	(−3.58)	(−3.40)	(−3.49)	(−0.34)	(2.77)	(−3.21)	(−3.11)	(−3.30)	(−0.44)	(3.43)	(−3.44)	(−3.32)	(−3.59)

This table reports the momentum profits with the removal of stocks with extreme absolute strength or extreme relative strength. In Panel A, we construct the winner and loser portfolios based on PR12 and exclude stocks with absolute strength ranked at the top *n*% from the winner portfolio and those with absolute strength ranked at the bottom *n*% from the loser portfolio. The remaining stocks within the winner and loser portfolios are held with equal weights for the subsequent 1, 6, and 12 months starting from month *t*. The enhanced momentum profit is calculated as the return difference between winner and loser portfolios. In Panel B, we construct the similar strategy by forming momentum portfolios based on PR12 and exclude extreme stocks according to their values of PR12. In Panels C and D, we form absolute strength momentum with the removal of stocks with extreme absolute strength and relative strength, respectively. Numbers in the parentheses are the *t*-statistics calculated using Newey and West's (1987) robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

3.1. Enhanced momentum strategies with removal of extreme past performances

We follow Yang and Zhang (2019) to develop enhanced momentum strategies in the following way. For a given month *t*, we allocate individual stocks into decile portfolios according to their values of PR12. For the JT winner portfolio that includes stocks with PR12 ranked at the top 10% in month *t*, we remove extreme absolute strength winners, that is, those with PR12 ranked at the top *n*% of the historical distribution. The remaining stocks are defined as enhanced JT winners. By the same token, we identify enhanced JT losers by removing absolute strength losers with PR12 ranked at the bottom *n*% of the historical distribution from the JT loser portfolio (those with PR12 ranked at the bottom 10%) in month *t*. Here we set $n = 1, 2, 3, 4$, and 5 to observe how the momentum returns vary with the breakpoints of extreme absolute strength. The enhanced JT momentum profit is then defined as the return difference between enhanced JT winners and losers with holding periods of 1, 6, and 12 months, respectively.

It should be noted that the removal of stocks with extreme absolute strength from the winner or loser JT momentum portfolio may cause insufficient observations in the portfolio, especially when *n* increases. If there is no stock within the enhanced JT winner or loser portfolio for a given month, we set the risk-free rate as the return of that portfolio in that month. This mechanism is also consistent with Yang and Zhang's (2019) principle of avoiding stocks with extreme returns.

Panel A of Table 2 reports the average and risk-adjusted returns of enhanced JT winners, losers, and the enhanced JT momentum strategy with different sets of *n* and different holding lengths. For the 1-month holding period, the average returns of the enhanced JT momentum are 0.341%, 0.728%, 1.023%, 0,782%, and 0.899% when 1%–5% stocks with extreme absolute strength are removed. The momentum profit becomes significant under the 10% significance level with the removal of more than 1% stocks with extreme absolute strength, and this pattern is consistent under risk adjustments. When we extend the holding length to 6 or 12 months, this pattern remains unchanged.

Yang and Zhang (2019) propose that holding stocks with less extreme past returns is not the only way for the enhanced momentum to be effective, an alternative way is to completely avoid the entire long or the short position that is replaced by the risk-free rate because they are subject to considerable loss due to market turnaround. For our strategy, the numbers of months of the long position (winner portfolio) replaced by the risk-free rate are 0, 3, 5, 8, and 14 with corresponding percentages of 0, 0.86%, 1.44%, 2.3%, and 4.02% when the breakpoint of absolute strength is set to be 1%–5%, respectively. The corresponding numbers of months of the short position (loser portfolio) replaced by the risk-free rate, however, are 3, 10, 30, 46, and 55 with corresponding percentages of 0.86%, 2.87%, 8.62%, 13.22%, and 15.81%, respectively. This observation is consistent with Yang and Zhang's (2019) evidence that a potential advantage of the enhanced momentum is to mitigates the loss by completely avoiding the entire position that is likely to experience momentum reversal, especially for the loser portfolio.

To examine the uniqueness of the enhanced momentum with removal of extreme absolute strength, we construct three alternative strategies for comparison. The first strategy removes stocks with extreme relative strength from the JT momentum. In particular, we remove stocks with PR12 values allocated in the top (bottom) *n*% from the JT winner (loser) decile. The second strategy removes stocks with extreme absolute strength from the absolute strength momentum, and the last one involves a strategy that removes stocks with extreme relative strength from the absolute strength momentum. Panels B to D of Table 2 give the raw and risk-adjusted returns for the three strategies, respectively.

As Panels B and C reveal, removing extreme relative strength from the JT momentum or removing stocks with extreme absolute strength from the absolute strength momentum does not generate significant momentum profits, regardless of the breakpoints used. What surprises us is that removing stocks with extreme relative strength from the absolute strength momentum generates significantly negative returns when the breakpoint is set to be more than 2%, as shown in Panel D. This finding apparently suggests that the "pure" absolute strength winners and losers that did not significantly outperform other stocks in the most recent period tend to exhibit reversals.

It should also be noted that while removing 5% stocks with extreme absolute strength enables the JT momentum to obtain the most significant profits, the 3% exclusion is able to produce an average return of more than 1% per month for the enhanced JT momentum across different holding lengths. To verify the effectiveness of using 3% breakpoints to identify extreme absolute strength, in Fig. 2 we plot the standard deviations and average future 12-month returns against the percentiles of stock-level past returns calculated from month t - 12 to month t - 1. We also provide the same plot with the removal of stocks having absolute strength at the top and bottom 3%. Consistent with Fig. 1, the standard deviations are calculated using weekly return data over future 12 months starting from month *t*. For the average future returns, we observe a flat pattern across percentiles of past returns, as represented by the red dots. When stocks with extremely high and low absolute strength are removed, we observe an upward trend of future returns as past returns increase, as represented by the blue dots. In terms of standard deviations, we also find that extreme past-return percentiles become less volatile with the removal of extreme absolute strength. Overall, Fig. 2 confirms the effectiveness of the 3% removal of extreme absolute strength in enhancing momentum patterns and reducing volatility of future performance. In subsequent analyses, we thus focus on the results using 3% breakpoints as the main strategy. In addition, we present the results based on the 6-month holding period to conserve space.[7]

The volatility-orientated argument provides plausible explanation for the evidence in Panel D of Table 2 that the removal of stocks with extreme relative strength from the absolute strength momentum generates significantly negative returns. If the underperformance is induced because of higher volatility of future returns, the exclusion of stocks with extreme relative strength would make absolute strength winners and losers more volatile. To confirm this conjecture, in Fig. 3 we plot the standard

[7] The evidence based on alternative breakpoints and holding periods is quite consistent and is available upon request.

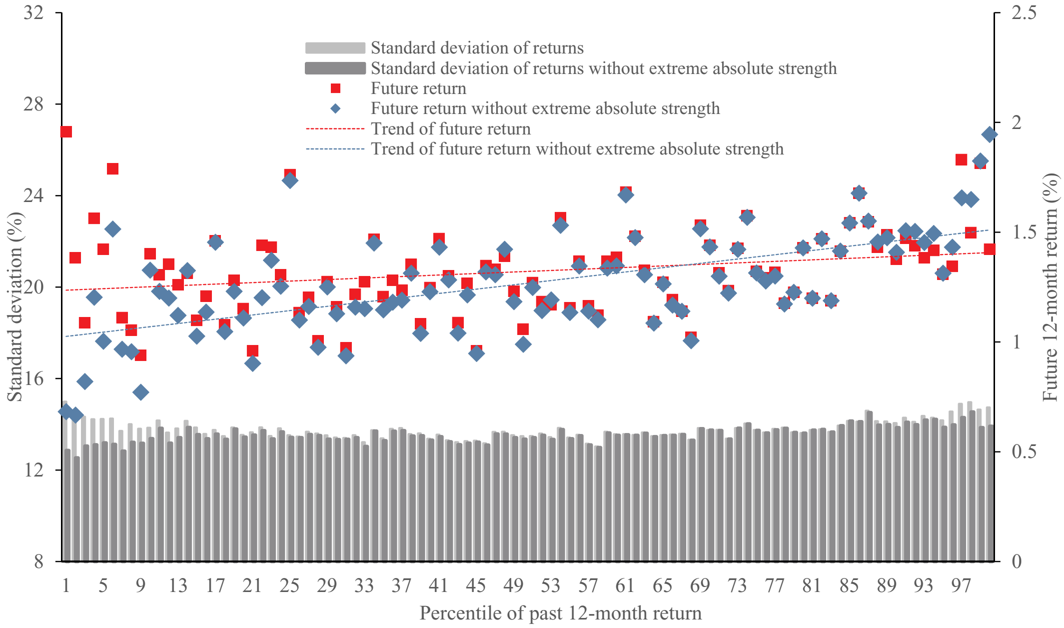

Fig. 2. Relative strength and future performance

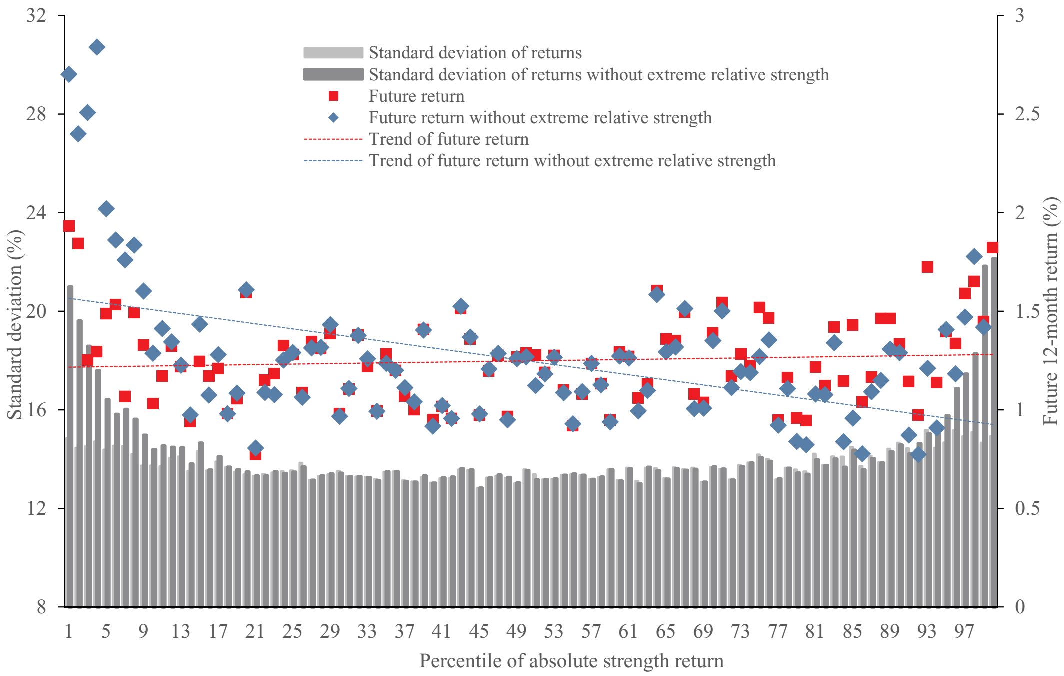

Fig. 3. Absolute strength and future performance

deviations and average future 12-month returns against the percentiles of absolute strength, with and without the removal of stocks with extreme relative strength. The blue dots exhibit a downward trend between future returns and absolute strength when stocks with extremely high and low relative strength are removed, consistent with the evidence of Panel D. More importantly, extreme absolute strength percentiles become more volatile with the removal of extreme relative strength. This observation confirms our conjecture that the exclusion of stocks with extreme relative strength make absolute strength winners and losers more volatile.

Table 3
Robustness of enhanced momentum profits.

	Winner	Loser	WML	FF3 alpha	FF5 alpha
January months	3.904*	1.191	2.713	1.739	1.674
	(1.80)	(0.60)	(1.70)	(1.07)	(0.91)
Non-January months	1.603***	0.373	1.231**	1.079*	1.264*
	(2.95)	(0.74)	(2.22)	(1.95)	(1.68)
The 1980/01–2018/12 period	1.969***	0.437	1.532***	1.301***	1.238***
	(4.58)	(1.10)	(3.63)	(3.52)	(3.21)
Skipping 1 month	1.814***	0.481	1.333**	1.170**	1.319*
	(3.35)	(0.96)	(2.38)	(2.04)	(1.74)
Enhanced JT momentum based on PR6	1.472***	−0.008	1.480***	1.252***	0.952**
	(2.77)	(−0.01)	(2.96)	(2.86)	(2.22)
JT momentum based on PR6	0.657	0.622	0.035	0.119	−0.113
	(1.10)	(0.92)	(0.10)	(0.37)	(−0.35)

This table reports the JT momentum profits based on the 6-month holding period with the removal of stocks with extreme absolute strength at the 3% breakpoint. We provide several robustness checks. First, we report the results separately for January-only and non-January subsamples. Second, we report the results for the 1980/01–2018/12 period. Third, we impose the 1-month skip between formation and holding periods. Finally, we evaluate past returns based on the cumulative returns (PR6) from month $t - 6$ to month $t - 1$. We report the results based on PR6 for the enhanced JT momentum and the standard JT momentum strategies, respectively. Numbers in the parentheses are the *t*-statistics calculated using Newey and West's (1987) robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

3.2. Robustness of the enhanced momentum profitability

To ensure the profitability of the enhanced momentum profitability, we consider several robustness tests and present the results in Table 3. First, while the JT momentum is prone to substantial losses in January months in Taiwan, the enhanced JT momentum generates consistent returns in both January and non-January subsamples; they are 2.712% and 1.231%, respectively. Thus the enhanced JT momentum reveals no January seasonality. Second, we extend the evaluation period back to January 1980 while leaving the period from January 1971 to December 1979 to construct the initial breakpoints. The enhanced JT momentum yields an average return of 1.532% per month with a *t*-statistic of 3.63. Thus the finding is robust to the earlier period. Third, Chen (1993) shows that the imposition of price limits of the Taiwan stock market could induce positive serial autocorrelation of stock returns. To ensure that the profitability of the enhanced JT momentum is unaffected by the mechanism of price limit, we impose a 1-month skip between formation and holding periods.[8] The average momentum profit is 1.333% and is significant at the 5% level. The adjusted returns remain significant and the overall magnitudes are quantitatively and statistically similar to the returns without the 1-month skip as reported in Panel A of Table 2. Finally, we repeat the analyses using the past 6-month cumulative returns from month t - 6 to month t - 1, denoted as PR6, to form relative and absolute strength measures. The standard JT and enhanced JT strategies constructed based on PR6 generate average returns of 0.035% and 1.480%, respectively. Thus our results are unaffected by the way we define past performance. Overall, we show that the enhanced JT momentum performs quite robust in the Taiwan stock market.

3.3. Cross-sectional regressions

So far we have demonstrated that the removal of stocks with extreme absolute strength from the JT momentum portfolios could enhance momentum profitability and reduce the volatility of future performance. The question remained is whether the unprofitability of the JT momentum in Taiwan is really attributed to the high volatility of stocks with extreme absolute strength. To address this issue, we perform the following cross-sectional regressions:[9]

$$R_{t+1,t+k} = \alpha + \beta \times PR12_{t-1} + \gamma \times EAS_{t-1} \times PR12_{t-1} \times \sigma_{t-1} + \varepsilon_{t+1,t+k}, \quad (1)$$

where $R_{t+1,t+K}$ is stock *i*'s return from month $t + 1$ to $t + K$, with $K = 1$, 6, and 12; $PR12_{t-1}$ is stock *i*'s cumulative return over past 12 months starting from month $t-$ 1; EAS_{t-1} is an indicator of stocks with extreme absolute strength; σ_{t-1} is stock *i*'s standard deviation using weekly return data over past 12 months starting from month t - 1. Here we adopt two definitions of EAS_{t-1}. The first identification sets the indicator for stocks with absolute strength ranked at the top and bottom 3% to be 1 and zero otherwise. The second identification sets the indicator for JT winners and losers with absolute strength ranked at the top and bottom 3% simultaneously to be 1 and zero otherwise. We perform the cross-sectional regressions of Eq. (1) every month and test the average slope coefficients using Newey and West's (1987) robust standard errors. If the unprofitability of the JT momentum is induced by the extremely high volatility of stocks with extreme absolute strength, the coefficient of γ is expected to be significantly negative.

Table 4 reports the regression results of Eq. (1) with Models (1) and (2) representing the two sets of EAS_{t-1} definitions. Consistent with our prediction, the γ coefficients are all negative and are significant in most cases across different holding lengths and different definitions of EAS_{t-1}. This finding indicates that stocks with extreme absolute strength and extremely high volatility reveal a negative

[8] We thank the referee for suggesting this analysis.
[9] We thank the referee for suggesting this analysis.

Table 4
Cross-sectional regressions.

	Model (1)			Model (2)		
Variable	$K = 1$	$K = 6$	$K = 12$	$K = 1$	$K = 6$	$K = 12$
Intercept	0.859	0.830**	0.915***	0.852	0.821**	0.908***
	(1.58)	(2.25)	(3.97)	(1.57)	(2.23)	(3.95)
PR12	2.050	1.067	0.684	1.368	0.804	0.499
	(1.61)	(1.61)	(1.45)	(1.19)	(1.30)	(1.11)
EAS × PR12 × σ	−0.190**	−0.097**	−0.060*	−0.182**	−0.078*	−0.046
	(−2.13)	(−2.06)	(−1.73)	(−2.06)	(−1.70)	(−1.30)

This table reports the cross-sectional regressions of future returns, which take the following form: $R_{t+1,\ t+k} = \alpha + \beta \times PR12_{t-1} + \gamma \times EAS_{t-1} \times PR12_{t-1} \times \sigma_{t-1} + \varepsilon_{t+1,\ t+k}$
where $R_{t+1,t+6}$ is stock i's return from month t to $t + K$, with $K = 1$, 6, and 12; $PR12_{t-1}$ is stock i's cumulative return over past 12 months starting from month $t - 1$; EAS_{t-1} is an indicator of stocks with extreme absolute strength; σ_{t-1} is stock i's standard deviation using weekly return data over past 12 months starting from month $t - 1$. We adopt two definitions of EAS_{t-1}. The first identification (Model (1)) sets the indicator for stocks with absolute strength ranked at the top and bottom 3% to be 1 and zero otherwise. The second identification (Model (2)) sets the indicator for JT winners and losers with absolute strength ranked at the top and bottom 3% simultaneously to be 1 and zero otherwise. We perform the cross-sectional regressions every month and test the average slope coefficients. Numbers in the parentheses are the t-statistics calculated using Newey and West's (1987) robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

relation between past and future performances, which results in the unprofitability of the JT momentum in Taiwan.

3.4. Time-series patterns of the enhanced momentum profitability

Yang and Zhang (2019) document that the major advantage of removing stocks with extreme absolute strength from the JT momentum is that it effectively alleviates the problem of momentum crashes and enables the JT momentum to be profitable for periods during which momentum has vanished. While we have demonstrated the effectiveness of the enhanced momentum in the Taiwan stock market, the next task is to explore the stability of its profitability over time.

We first consider the impact of market states, which is initiated by Cooper et al. (2004). In particular, they indicate that the JT momentum is profitable only following up markets because investor biases are more accentuated after market gains. Applying Cooper et al.'s (2004) analyses to the Taiwan stock market, Du et al. (2009) point out that the unprofitability of momentum in Taiwan is due to the frequency and severity of down markets. Concentrating on periods following up markets, they find that the JT momentum is profitable in Taiwan.

To consider the effect of market states, we calculate the cumulative return on the TAIEX index over the past 12 months ending in month t - 1. If this return is nonnegative (negative), we define month t as up (down) market. We next perform the following time-series regression:

$$WML_t = \alpha + \beta \times UP_t + \varepsilon_t, \tag{2}$$

where WML_t is the monthly return of the JT or enhanced JT momentum with a 6-month holding period in month t; UP_t is an indicator of up market which equals one if month t is classified as up market and zero otherwise. We also include risk factors in the regression for risk adjustments, expressed as follows:

$$WML_t = \alpha + \beta \times UP_t + \sum_{j=1}^{J} \gamma \times F_{j,t} + \varepsilon_t, \tag{3}$$

where $F_{j,t}$ represents the jth factor of the Fama and French (1993, 2015) three- or five-factor models. In these model specifications, α represents the momentum return following down markets while β captures the incremental momentum profitability following up markets beyond down markets. According to Cooper et al. (2004) and Du et al. (2009), the estimations of β from the equations are positive and significant for the JT momentum. In addition to the entire momentum portfolio, we also perform the regressions using the returns of the winner and loser portfolios as the dependent variable.

The first two columns of Table 5 present the regression results of JT and enhanced JT momentum, respectively, with Panels A to C showing the estimation results of Eq. (2) using winner, loser, and the entire momentum portfolios as the dependent variable whereas Panels D and E showing the estimation results of Eq. (3) for the Fama and French (1993, 2015) three- and five-factor models using the entire momentum portfolios as the dependent variable. Column (1) indicates the β coefficients are 0.566 and −0.231 for winner and loser portfolios, resulting a positive β coefficient of 0.797 for the JT momentum. The β coefficient becomes significant at 1.473 (t-statistic = 2.17) under the Fama and French's (1993) risk adjustment and becomes 1.239 (t-statistic = 1.85) under the Fama and French's (2015) risk adjustment. The corresponding α coefficients under risk adjustments are −0.972% (t-statistic = −1.78) and −1.094% (t-statistic = −2.06) per month, respectively. These observations are consistent with the finding of Du et al. (2009).

The results for the enhanced JT momentum, as reported in column (2), are different from those observed from column (1) in several aspects. First, the β coefficients of winner and loser portfolios reverse to be negative and positive while insignificant, respectively. Second, the β coefficient of the enhanced JT momentum is −1.236 (t-statistic = −1.22) and remains insignificant when

Table 5
Time-series patterns of momentum strategies.

	Market states	Market dynamics	Market volatility	Momentum crashes				
	JT	Enhanced JT	JT	Enhanced JT	JT	Enhanced JT	JT	Enhanced JT
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Raw returns of winner portfolio								
α	0.168	2.029**	3.160***	3.490***	1.186**	1.637***	−0.591	1.041*
	(0.14)	(2.05)	(3.62)	(6.08)	(1.99)	(2.90)	(−0.92)	(1.95)
β	0.566	−0.363	−2.942**	−2.525**	−1.466	0.673	9.987***	8.203***
	(0.43)	(−0.32)	(−2.26)	(−2.52)	(−1.14)	(0.54)	(4.96)	(5.01)
Panel B: Raw returns of loser portfolio								
α	0.823	−0.142	2.181**	2.657***	0.683	1.067**	−0.641	0.142
	(0.66)	(−0.15)	(2.46)	(4.33)	(1.12)	(2.08)	(−0.97)	(0.28)
β	−0.231	0.873	−0.974	−3.579***	0.097	−1.688	11.364***	3.393*
	(−0.17)	(0.82)	(−0.67)	(−3.82)	(0.07)	(−1.37)	(4.99)	(1.83)
Panel C: Raw returns of WML portfolio								
α	−0.654	2.171**	0.980*	0.833**	0.503	0.570**	0.051	0.900*
	(−1.23)	(2.06)	(1.75)	(2.54)	(1.31)	(2.05)	(0.14)	(1.86)
β	0.797	−1.236	−1.969**	1.054	−1.564*	2.361	−1.377	4.809**
	(1.10)	(−1.22)	(−2.12)	(1.33)	(−1.83)	(1.63)	(−1.07)	(2.14)
Panel D: FF3 − adjusted returns of WML portfolio								
α	−0.972*	1.773**	1.129**	0.373	0.720*	0.427	0.226	0.943*
	(−1.78)	(1.97)	(2.14)	(0.84)	(1.87)	(1.52)	(0.64)	(1.88)
β	1.473**	−0.820	−2.068**	1.609*	−1.939**	2.343*	−2.366**	3.269*
	(2.17)	(−0.96)	(−2.13)	(1.72)	(−2.55)	(1.71)	(−2.08)	(1.83)
Panel E: FF5 − adjusted returns of WML portfolio								
α	−1.094**	1.847*	1.005*	0.444	0.326	0.596	−0.062	1.116
	(−2.06)	(1.81)	(1.90)	(0.86)	(0.85)	(1.40)	(−0.18)	(1.62)
β	1.239*	−0.730	−2.091**	1.604*	−1.598**	2.196*	−2.191*	2.814*
	(1.85)	(−0.86)	(−2.15)	(1.86)	(−2.13)	(1.76)	(−1.88)	(1.77)

This table reports the time-series regressions for the JT momentum and enhanced momentum. In particular, we perform the following regressions: $WML_t = \alpha + \beta \times Dum_t + \varepsilon_t$ and $WML_t = \alpha + \beta \times Dum_t + \Sigma_{j=1}{}^{J}\gamma \times F_{j,\ t} + \varepsilon_t$
where WML_t is the monthly return of the JT or enhanced JT momentum with a 6-month holding period in month t; Dum_t represents up-market dummy, market transition dummy, high market volatility dummy, and panic-state dummy in each model specification. We report the α and β coefficients from each regression. Numbers in the parentheses are the t-statistics calculated using Newey and West's (1987) robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

the two factor models are taken into account. Finally, the α coefficient of the enhanced JT momentum is significant at 2.171% (t-statistic = 2.06) and remains significantly positive under risk adjustments. The main implications from column (2) include that (i) the enhanced JT momentum is not prone to losses following down markets, and that (ii) market states do not affect the profitability of the enhanced JT momentum.

We next investigate whether the enhanced JT momentum profits vary with market dynamics. This analysis is motivated by the evidence from both U.S. and Taiwan markets that momentum is more profitable when the market continues in the same direction because investor overconfidence is accelerated by confirming the movement of the market (Asem and Tian, 2010; Lin et al., 2016). We first follow the two studies to define a given month t as up (down) market if the cumulative return on the TAIEX index over t - 12 to t - 1 is nonnegative (negative). Following up (down) market, if the subsequent return of the TAIEX index in month t is nonnegative (negative), we define it as market continuation. On the contrary, if a nonnegative (negative) cumulative TAIEX return over t - 12 to t - 1 is followed by negative (nonnegative) return in month t, we define it as market transition. We identify a dummy variable of market transition, $Tran_t$, which equals one if month t is classified as market transition and zero otherwise. We then replace UP_t with $Tran_t$ in Eqs. (2) and (3) and report the regression results in columns (3) and (4) of Table 5.

Consistent with Lin et al.'s (2016) finding, we show that the standard JT momentum earns significantly positive returns during periods of market continuations and is prone to substantial losses during periods of market transitions. This is observable from the significantly positive α coefficients and the significantly negative β coefficients in Panels C to E. The α and β coefficients of the enhanced JT momentum, however, are both positive, suggesting that the removal of stocks with extreme absolute strength enables the JT momentum to be free from the losses when the market reverses.

Wang and Xu (2015) and Daniel and Moskowitz (2016) both propose market volatility as a useful predictor of momentum profitability. Taking advantage of the observation that extreme market volatility during the financial crisis is followed by dramatic losses of momentum strategies, they empirically show that the JT momentum is profitable following periods of low market volatility but not following periods of high market volatility. To identify whether the market is volatile, we follow Wang and Xu's (2015) procedure to calculate two sets of past market volatility. At the beginning of each month t, we calculate the short-term (long-term) market volatility by computing the standard deviation of the TAIEX daily returns over month $t - 12$ to month $t - 1$ (month $t - 36$ to month $t - 1$). We define a high-volatility dummy for month t, $HVol_t$, which equals one if the short-term market volatility is greater than the long-term market volatility and zero otherwise. Again, we replace UP_t with $HVol_t$ in Eqs. (2) and (3) and report the regression results in columns (5) and (6) of Table 5.

Column (5) reveals that Wang and Xu's (2015) observation is applicable to the Taiwan stock market in that the JT momentum generates remarkably lower returns following periods of high market volatility; the β coefficients are all negative and significant in Panels C to E. This pattern, however, is reversed for the enhanced momentum, as presented in column (6); it yields positive β coefficients regardless of risk adjustments. Thus the removal of stocks with extreme absolute strength also avoids losses when the market is extremely volatile.

3.5. Momentum crashes and the enhanced momentum

A major critique of the standard JT momentum is that it is subject to infrequent but severe negative returns (Daniel and Moskowitz, 2016), which makes it too risky and less desirable to investors. Yang and Zhang (2019) suggest that the removal of stocks with extreme absolute strength is an effective way to avoid such crash risk in the U.S. markets. In this subsection, we also examine whether the occurrence of momentum crashes can be effectively reduced by removing stocks with extreme absolute strength in the Taiwan stock market.

Daniel and Moskowitz (2016) observe that the momentum crashes occur in panic states, that is, following market declines that are contemporaneous with market rebounds, and when market volatility is high. We thus follow this criterion by defining a crash dummy, $Crash_t$, which equals one if the TAIEX return over $t - 12$ to $t - 1$ is negative that is contemporaneous with a positive TAIEX return in month t, and when the short-term market volatility is greater than the long-term market volatility, and it is zero otherwise. By replacing UP_t with $Crash_t$ in Eqs. (2) and (3), we show in column (7) that the JT momentum also shows remarkably negative returns in panic states; the β coefficients are highly negative and are significant under risk adjustments. However, the enhanced JT momentum, as presented in column (8), has significantly positive β coefficients regardless of risk adjustments. Outside the infrequent panic states, the enhanced JT momentum still generates significantly positive returns. This finding thus suggests that Yang and Zhang's (2019) argument also conforms to the Taiwan stock market.

We next explore how the selection of breakpoints in determining extreme absolute strength is related to the resolution of the momentum crashes. To this end, we list the ten worst monthly returns of the JT momentum based on the 6-month holding period within our observation period, January 1990 to December 2018. They are reported in Table 6. We also report the returns for the enhanced JT momentum based on the removal of 1%–5% stocks with extreme absolute strength in each of the corresponding crash months.

When no stocks are removed from the decile momentum portfolio, the JT momentum has the worst monthly return of −48.655% in January 2000. This loss is substantially mitigated to −10.074% when 1% stocks with extreme absolute strength are removed. This return is reversed to be positive when more than 2% stocks with extreme absolute strength are removed, and it can be as large as 30.251% with the 4% removal. This pattern retains for all of the ten worst monthly JT momentum returns. As a result, the average return of the ten month with worst performances is −21.839% per month, and it increases uniformly to −6.805%, −5.143%, −0.467%, 1.607%, and 2.474% when 1%–5% stocks with extreme absolute strength are removed. This finding again strengthens the advantage of the enhanced JT momentum by mitigating the substantial losses during crash periods.

Table 6
Worst monthly returns of the JT momentum.

		Breakpoints of extreme absolute strength					
	Month	0%	1%	2%	3%	4%	5%
1 (Worst)	200001	−48.655	−10.074	5.296	15.613	30.251	24.620
2	200204	−25.667	−8.203	−8.514	−8.063	−7.087	−12.122
3	200203	−20.232	−7.191	−7.014	−0.998	6.797	0.554
4	200108	−19.545	−10.319	−9.046	−8.458	−0.750	−0.603
5	199001	−18.708	−3.966	−16.543	−16.543	−16.543	−16.543
6	200012	−18.706	−10.910	−15.424	−15.377	−15.256	−15.499
7	199710	−18.532	−6.080	−6.389	−6.464	−6.015	6.173
8	199709	−17.170	−9.279	−10.352	−10.160	−7.539	4.138
9	200903	−15.954	−1.311	−0.991	21.037	22.778	24.580
10	200102	−15.222	−0.719	17.542	24.744	9.435	9.439
Average	–	−21.839	−6.805	−5.143	−0.467	1.607	2.474

This table report the ten worst monthly returns of the standard JT momentum. For each month with worst performance, we also report the return of the enhanced momentum with the removal of stocks featured by extreme absolute strength at the 1% to 5% breakpoints.

4. Extreme absolute strength and cross-sectional attributes of momentum

So far we have demonstrated the profitability of the enhanced JT momentum and its stability over time. In this section, we examine whether the removal of stocks with extreme absolute strength affects the pricing ability of cross-sectional attributes in terms of generating intermediate-term return continuations.

4.1. Cross-sectional attributes of momentum

Several studies evidenced by the U.S. stock markets have verified the effectiveness of certain firm-level characteristics in explaining the cross-sectional variations of momentum. In particular, Sagi and Seasholes (2007) establish the linkage between growth options and momentum profits, with market-to-book ratio as a proxy for growth options. Zhang (2006) shows that information uncertainty enhances momentum profitability, where high return dispersion, smaller market capitalization, younger age, lower analyst coverage correspond to higher magnitude of information uncertainty. Lee and Swaminathan (2000) document a positive relation between turnover and momentum profits. Finally, Hou et al. (2013) develop a standard rational expectations model to describe the negative relation between R^2 and momentum profits.

Beyond these cross-sectional attributes, Bandarchuk and Hilscher (2013) highlight the importance of return dispersion in measuring extreme past returns for momentum profitability. They show that the explanatory power of several firm characteristics disappears once the effect of return dispersion is controlled for. While the competing explanatory ability between return dispersion and firm characteristics has yet been explored in the Taiwan stock market, our paper serves as the first study to fill this gap in the literature.

We follow Bandarchuk and Hilscher (2013) by considering the following variables:

(1) Return dispersion: Bandarchuk and Hilscher (2013) propose two measures of return dispersion at the firm level. The first one is a proxy of idiosyncratic volatility (IVOL) developed by Hou et al. (2013), which involves a regression that includes the TAIEX return and industry returns. We use the industry classifications given by TSE to form 32 industry portfolios that are constructed based on value weights. For each holding month t of momentum, we perform the following time-series regressions for each individual stock:

$$R_{i,d} = \alpha_i + \beta_i \times r\mathrm{R}_{m,d} + \gamma_i \times R_{I,d} + e_{i,d}, \tag{4}$$

where $R_{i,d}$ is the log return of stock i in week d; $R_{m,d}$ is the log return of the TAIEX index in week d; $R_{I,d}$ is the log return of the industry to which stock i belongs in week d. The regressions are estimated using weekly returns from Wednesday to Wednesday for the 52 weeks prior to month t. IVOL is calculated as the standard deviation of residual returns.

The second measure, defined as momentum strength (Mom_strength), is calculated as the absolute value of the difference between the stock's past 12-month return and the median return over the same period:

$$Mom\_strength_{i,t} = exp(|R_{i,t-12,t-1} - R_{median,t-12,t-1}|) - 1, \tag{5}$$

where $R_{i,t-12,t-1}$ is the log return of stock i from month $t-12$ to $t-1$; $R_{median,t-12,t-1}$ is the median across all stocks. Bandarchuk and Hilscher (2013) argue that IVOL and Mom_strength both measure the extent to which past returns are extreme.

(2) Market-to-book (MB) ratio: For each July of the year to June in the next year, we follow Sagi and Seasholes (2007) by defining MB as the ratio of market capitalization to book equity of common stocks measured at the end of prior fiscal year. Following Fama and French (1996), firms with negative book equity are excluded from the sample.
(3) Forecast dispersion (DISP): We measure DISP as the standard deviation of earnings per share (EPS) forecasts divided by the average EPS forecasts using analysts' forecasts in the most recent quarter. Firms to be included must have at least two forecasts in that quarter.
(4) Turnover (TURN): For each holding month t, we calculate average monthly return turnover as the monthly number of shares traded divided by the number of shares outstanding averaged from month $t-12$ to $t-1$.
(5) Illiquidity (ILLIQ): We calculate the daily Amihud (2002) illiquidity measure by computing the absolute value of daily return divided by daily dollar trading volume. ILLIQ is then computed as the average of the daily Amihud (2002) measure over past 12 months.
(6) Firm size (SIZE): We use a stock's market capitalization at the end of previous month to measure its SIZE.
(7) Firm age (AGE): AGE is the number of years since the date of the firm's IPO.
(8) R^2: The return R^2 is obtained as the adjusted R^2 from the same regression we use to calculate IVOL.
(9) Share price (PRICE): As another liquidity measure, we use the share price of the stock at the end of previous month to proxy for transaction costs and limits to arbitrage.
(10) Analyst coverage (COVERAGE): COVERAGE is defined as the number of analysts following the firm in the most recent quarter.

To control for the influence of outliers, we winsorize the data for all variables at the 0.5% and 99.5% levels. To examine whether these firm-level attributes explain momentum profits, for each month t we conduct a dependent sorting procedure by first sorting individual stocks into quintiles by one of the variables and then into deciles by PR12. Within each quintile of the attribute (P1–P5), we calculate momentum profits as the return difference between winner and loser deciles with a 6-month holding period. To analyze

Table 7
JT momentum profits sorted by volatility and characteristics.

	P1	P2	P3	P4	P5	Diff	FF3 Diff	FF5 Diff
IVOL	−0.007	0.150	0.307	0.104	0.077	0.084	0.124	0.112
	(−0.04)	(0.80)	(1.60)	(0.52)	(0.29)	(0.31)	(0.49)	(0.43)
Mom_strength	0.047	0.207	0.114	0.101	−0.137	−0.184	−0.131	−0.299
	(0.34)	(1.40)	(0.66)	(0.57)	(−0.43)	(−0.59)	(−0.46)	(−1.05)
MB	−0.084	0.165	0.098	0.249	0.142	0.226	0.186	0.006
	(−0.46)	(0.82)	(0.59)	(1.16)	(0.66)	(0.92)	(0.77)	(0.02)
DISP	−0.227	−0.357	−0.216	−0.213	0.020	0.247	0.292	0.369
	(−0.88)	(−1.63)	(−0.96)	(−0.85)	(0.08)	(0.85)	(1.07)	(1.33)
TURN	−0.015	0.335 *	0.118	0.128	−0.025	−0.011	−0.011	−0.105
	(−0.08)	(1.79)	(0.65)	(0.61)	(−0.11)	(−0.04)	(−0.04)	(−0.40)
ILLIQ	0.020	0.217	0.289	−0.006	0.044	0.024	0.013	0.062
	(0.10)	(1.17)	(1.38)	(−0.03)	(0.20)	(0.10)	(0.05)	(0.25)
SIZE	−0.053	0.309	0.189	−0.181	0.086	0.139	0.145	0.149
	(−0.23)	(1.41)	(0.84)	(−1.00)	(0.39)	(0.48)	(0.52)	(0.50)
AGE	0.287	−0.112	0.176	0.000	−0.074	−0.361	−0.337	−0.295
	(1.33)	(−0.53)	(0.86)	(0.00)	(−0.45)	(−1.44)	(−1.35)	(−1.17)
R^2	0.011	0.113	0.281	0.272	0.037	0.025	0.020	−0.017
	(0.06)	(0.54)	(1.36)	(1.36)	(0.18)	(0.10)	(0.08)	(−0.07)
PRICE	0.350 *	0.215	0.027	0.032	0.128	−0.222	−0.193	−0.280
	(1.68)	(0.90)	(0.13)	(0.16)	(0.72)	(−1.05)	(−0.91)	(−1.31)
COVERAGE	0.173	−0.418	0.125	−0.451 *	−0.509 *	−0.682 ***	−0.746 ***	−0.642 **
	(0.69)	(−1.20)	(0.42)	(−1.95)	(−1.87)	(−2.91)	(−2.97)	(−2.29)

This table reports the JT momentum profits sorted by several firm-level attributes. For each month *t*, we conduct a dependent sorting procedure by first sorting individual stocks into quintiles by one of the variables and then into deciles by PR12. Within each quintile of the attribute (P1–P5), we calculate momentum profits as the return difference between winner and loser deciles with a 6-month holding period. We also calculate the difference in momentum profits between P5 and P1 quintiles. Numbers in the parentheses are the *t*-statistics calculated using Newey and West's (1987) robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

whether the attribute is effective in explaining momentum profits, we compute the difference in momentum profits between P5 and P1. It should be noted that IVOL, Mom_strength, MB, DISP, TURN, and ILLIQ are documented to be positively correlated with momentum profits, thus the difference in momentum profits between P5 and P1 are expected to be positive. Nevertheless, as SIZE, AGE, PRICE, and COVERAGE are negatively correlated with momentum profits, their difference in momentum profits between P5 and P1 are expected to be negative.

Table 7 shows that the differences between P5 and P1 are all insignificant, with the only exception for COVERAGE. Even for the COVERAGE measure, none of the quintile groups exhibits significantly positive momentum profits; the significant difference in momentum profits between P5 and P1 mainly comes from the negative momentum profit of the P5 portfolio. That is, none of the 11 variables successfully produces significant differences in momentum profits. This finding does not change when the returns are adjusted using the two factor models.

4.2. Cross-sectional attributes and enhanced momentum

We build a further extension of Bandarchuk and Hilscher (2013) by investigating whether the removal of stocks with extreme absolute strength changes the relation between momentum profitability and firm-level attributes. To this end, we use the same procedure described in Section 4.1 by forming 5 by 10 portfolios sorted firstly by each of the characteristics and then by PR12. For each of the winner (loser) portfolios within each characteristic quintile, we remove stocks with absolute strength ranked at the top (bottom) 3% of its historical distribution. We then form enhanced momentum and calculate its profits for each characteristic quintile.

The results are provided in Table 8, and two interesting findings are observed. First, the two measures of return dispersion that proxy for extreme past returns, are positively correlated with enhanced momentum profits with statistical significance. The P5 portfolios generate the highest enhanced momentum profits among the quintile portfolios formed based on IVOL and Mom_strength, resulting in significant differences in enhanced momentum profits between P5 and P1 portfolios especially when risk adjustments are considered. Second, AGE and COVERAGE, as proxies of information uncertainty, also produce significant differences in enhanced momentum profits, with the P1 portfolios generating the highest momentum profits among the two measures.

The findings from Table 8 are interesting and have important implications. First, while stocks with extreme absolute strength tend to have extremely high return volatilities, removing these stocks rebuilds the relation between past volatility and momentum profits. It also suggests that the absence of the volatility-momentum relation is attributed to the minority of stocks with extreme absolute strength. Second, return dispersion and information uncertainty both play important roles for the enhanced momentum profits, while other firm-level attributes still remain irrelevant to the momentum phenomenon. This finding also highlights the difference between

Table 8
Enhanced momentum profits sorted by volatility and characteristics.

	P1	P2	P3	P4	P5	Diff	FF3 Diff	FF5 Diff
IVOL	0.428	0.621*	0.915***	0.619	1.042**	0.614	0.684*	0.772*
	(1.29)	(1.67)	(2.86)	(1.60)	(2.36)	(1.53)	(1.76)	(1.87)
Mom_strength	0.644*	1.337***	1.089**	0.727*	1.642**	0.998*	1.108**	1.283**
	(1.66)	(2.81)	(2.12)	(1.72)	(2.52)	(1.97)	(2.09)	(2.18)
MB	0.873**	0.679**	0.586**	0.842**	0.684	−0.189	−0.174	−0.401
	(2.09)	(2.10)	(2.16)	(2.14)	(1.56)	(−0.52)	(−0.43)	(−0.96)
DISP	0.596	0.184	0.565	0.504	0.504	−0.092	−0.220	−0.219
	(1.29)	(0.36)	(1.27)	(1.13)	(1.12)	(−0.21)	(−0.53)	(−0.46)
TURN	0.515	0.695**	0.735**	1.162**	0.365	−0.150	−0.121	−0.134
	(1.51)	(2.26)	(2.34)	(2.40)	(1.00)	(−0.40)	(−0.34)	(−0.35)
ILLIQ	0.466	0.634*	0.475	0.789**	0.865**	0.399	0.353	0.538
	(1.41)	(1.94)	(1.32)	(2.30)	(2.41)	(0.97)	(0.98)	(1.64)
SIZE	0.682*	0.900**	0.894**	0.594	0.452	−0.231	−0.104	−0.167
	(1.91)	(2.38)	(2.49)	(1.51)	(1.36)	(−0.57)	(−0.27)	(−0.37)
AGE	1.476***	0.787*	0.878**	0.359	−0.110	−1.586***	−1.662***	−1.528***
	(2.97)	(1.81)	(2.19)	(1.40)	(−0.54)	(−3.12)	(−3.41)	(−3.14)
R^2	0.571*	0.624	0.616**	0.872***	0.726	0.155	−0.086	−0.273
	(1.74)	(1.42)	(1.99)	(2.65)	(1.53)	(0.39)	(−0.27)	(−0.79)
PRICE	0.704**	0.929**	0.909**	0.388	1.006**	0.302	0.252	0.134
	(2.22)	(2.35)	(2.48)	(1.04)	(2.20)	(0.70)	(0.61)	(0.30)
COVERAGE	0.592*	−0.480	0.532	0.096	−0.188	−0.780*	−0.855**	−0.621
	(1.80)	(−1.22)	(1.25)	(0.33)	(−0.46)	(−1.89)	(−2.01)	(−1.44)

This table reports the enhanced JT momentum profits sorted by several firm-level attributes. For each month *t*, we conduct a dependent sorting procedure by first sorting individual stocks into quintiles by one of the variables and then into deciles by PR12. For each of the winner (loser) portfolios within each characteristic quintile, we remove stocks with absolute strength ranked at the top (bottom) 3% of its historical distribution. Within each quintile of the attribute (P1–P5), we calculate momentum profits as the return difference between winner and loser deciles with a 6-month holding period. We also calculate the difference in momentum profits between P5 and P1 quintiles. Numbers in the parentheses are the *t*-statistics calculated using Newey and West's (1987) robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

U.S. and Taiwan markets in that the sources of the momentum phenomenon are distinct between the two markets. Finally, and perhaps the most important, we show that the removal of stocks with extreme absolute strength could change the relation between firm-level attributes and momentum, an interesting finding that is new to the momentum literature.

While we have demonstrated that return dispersion and information uncertainty are both important determinants of enhanced momentum in Taiwan, it is critical to analyze their competing explanatory abilities for the enhanced momentum profitability. We thus obtain the residual characteristic to isolate the impact of another characteristic and explore the pure explanatory ability of one attribute that is independent of another. To examine this issue, we first perform the cross-sectional regressions for each of the nine characteristics other than return dispersion on IVOL or Mom_strength, and then obtain the residual characteristic from the regressions each month. We next apply this residual characteristic to repeat the same analyses as we conduct in Table 8. Panels A and B of Table 9 present the results based on each residual characteristic that is independent of IVOL and Mom_strength, respectively.

It is notable that only AGE retains its explanatory ability in producing differences in the enhanced momentum profitability when the impact of IVOL or Mom_strength is controlled for. The enhanced momentum profits across quintiles formed by residual COVERAGE and the difference between P5 and P1 quintiles are all insignificant, suggesting that IVOL and Mom_strength are better predictors of enhanced momentum profits than COVERAGE. For attributes other than AGE and COVERAGE, the results remain unchanged compared with Table 8. Our finding thus concludes that AGE is the only characteristic that exhibit distinct explanatory ability for the enhanced momentum profitability.

The final task is to examine whether residual IVOL and residual Mom_strength still remain important determinants for the enhanced momentum profitability. Because AGE and COVERAGE are the only useful predictors of enhanced momentum, we use the two variables to obtain residual IVOL and residual Mom_strength. As Table 10 shows, the overall pattern that higher IVOL stocks exhibit higher enhanced momentum profits does not change when the incremental impact of AGE or COVERAGE is isolated. The results for Mom_strength, however, become weaker once the impact of AGE or COVERAGE is controlled for. Thus IVOL seems to be a more consistent measure of return dispersion that is able to distinguish the enhanced momentum profits.

5. Conclusions

The Taiwan stock market has been widely documented to be a remarkable exception of momentum. We show that the absence of momentum in Taiwan is attributed to stocks with extreme absolute strength that are highly volatile and more likely to exhibit reversal. An enhanced momentum strategy that removes these stocks from the typical momentum portfolios is able to generate

Table 9
Enhanced momentum profits sorted by residual characteristics.

	P1	P2	P3	P4	P5	Diff	FF3 Diff	FF5 Diff
Panel A: Residual characteristics obtained using IVOL								
MB	1.019**	0.363	0.544	0.934**	0.606	−0.413	−0.532	−0.781*
	(2.06)	(0.96)	(1.39)	(2.28)	(1.54)	(−1.05)	(−1.34)	(−1.82)
DISP	0.542	0.133	0.253	0.599	0.838*	0.296	0.134	0.127
	(1.45)	(0.36)	(0.57)	(1.34)	(1.94)	(0.70)	(0.30)	(0.25)
TURN	0.529	0.535*	0.429	1.144**	0.084	−0.445	−0.517	−0.613
	(1.45)	(1.84)	(1.39)	(2.58)	(0.30)	(−1.22)	(−1.37)	(−1.61)
ILLIQ	0.916**	0.708**	0.895**	0.958**	0.598*	−0.319	−0.215	−0.177
	(2.02)	(2.09)	(2.49)	(2.44)	(1.70)	(−1.05)	(−0.75)	(−0.58)
SIZE	0.536*	0.846**	0.817**	0.607	0.863**	0.327	0.292	0.324
	(1.81)	(2.51)	(2.11)	(1.61)	(2.41)	(0.86)	(0.81)	(0.77)
AGE	1.334***	0.551	0.613*	0.501	−0.263	−1.597***	−1.643***	−1.722***
	(2.85)	(1.45)	(1.66)	(1.65)	(−1.02)	(−3.02)	(−3.27)	(−3.00)
R^2	0.609*	0.975***	0.743**	1.042**	0.841	0.231	−0.021	−0.137
	(1.95)	(2.99)	(2.01)	(2.36)	(1.57)	(0.56)	(−0.06)	(−0.34)
PRICE	0.863**	0.680*	1.014***	−0.102	1.440***	0.577	0.295	0.132
	(2.24)	(1.68)	(2.92)	(−0.34)	(2.65)	(1.32)	(0.81)	(0.35)
COVERAGE	0.316	0.297	0.540	0.185	0.377	0.060	−0.134	−0.061
	(1.02)	(0.96)	(1.23)	(0.62)	(0.82)	(0.15)	(−0.37)	(−0.15)
Panel B: Residual characteristics obtained using Mom_strength								
MB	1.005*	1.070**	0.378	0.934**	1.143**	0.138	0.065	−0.018
	(1.94)	(2.53)	(0.83)	(2.24)	(2.06)	(0.41)	(0.19)	(−0.05)
DISP	0.575	0.392	0.434	0.516	0.993**	0.418	0.157	0.120
	(1.29)	(0.79)	(0.94)	(1.09)	(2.37)	(1.00)	(0.38)	(0.24)
TURN	0.452	0.645**	0.989**	0.729*	0.215	−0.237	−0.416	−0.436
	(1.32)	(2.28)	(2.57)	(1.79)	(0.63)	(−0.67)	(−1.03)	(−1.14)
ILLIQ	1.036**	0.465	0.485*	0.291	0.549*	−0.487	−0.543	−0.549
	(2.47)	(1.61)	(1.73)	(1.24)	(1.76)	(−1.16)	(−1.25)	(−1.08)
SIZE	0.794**	0.990***	0.794*	0.669	0.324	−0.470	−0.355	−0.310
	(2.12)	(2.72)	(1.80)	(1.55)	(0.83)	(−1.05)	(−0.90)	(−0.75)
AGE	1.016**	0.857**	0.559*	0.305	−0.174	−1.191**	−1.221***	−1.137**
	(2.23)	(2.33)	(1.83)	(1.18)	(−0.72)	(−2.47)	(−2.71)	(−2.38)
R^2	0.607*	0.828**	0.916**	0.939**	0.792**	0.185	0.211	0.013
	(1.83)	(2.23)	(2.14)	(2.08)	(1.98)	(0.52)	(0.59)	(0.04)
PRICE	0.827	0.955**	0.666*	0.401	1.183**	0.356	0.302	0.332
	(1.64)	(2.57)	(1.87)	(1.31)	(2.06)	(1.14)	(1.10)	(1.05)
COVERAGE	0.763*	0.371	0.512	0.370	0.345	−0.418	−0.505	−0.626
	(1.97)	(1.38)	(1.27)	(1.24)	(0.75)	(−1.16)	(−1.44)	(−1.64)

This table reports the enhanced JT momentum profits sorted by residual attributes. We first perform the cross-sectional regressions for each of the nine characteristics other than return dispersion on IVOL (Panel A) or Mom_strength (Panel B), and then obtain the residual characteristic from the regressions each month. For each month *t*, we conduct a dependent sorting procedure by first sorting individual stocks into quintiles by one of the residual characteristics and then into deciles by PR12. For each of the winner (loser) portfolios within each residual characteristic quintile, we remove stocks with absolute strength ranked at the top (bottom) 3% of its historical distribution. Within each quintile of the attribute (P1–P5), we calculate momentum profits as the return difference between winner and loser deciles with a 6-month holding period. We also calculate the difference in momentum profits between P5 and P1 quintiles. Numbers in the parentheses are the *t*-statistics calculated using Newey and West's (1987) robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

significant profits in the intermediate terms. The major advantages of the enhanced momentum strategy include its stable profitability over time and its substantial improvements during periods of momentum crashes.

We further contribute to the literature by showing that the removal of stocks with extreme absolute strength rebuilds the relation between firm-level attributes and momentum profitability. In particular, excluding stocks featured by extreme absolute strength makes return dispersion and information uncertainty interact with momentum profits positively, with idiosyncratic volatility and firm age being the most effective proxies. Further, the two attributes provide distinct sources of the enhanced momentum profitability.

Our study is important not only in terms of explaining the absence of momentum in Taiwan but also demonstrating two contributions to the literature. First, we show that a momentum strategy with the removal of stocks featured by extreme absolute strength is applicable to a market without the existence of momentum. This is an important extension of Yang and Zhang (2019). Second, the removal of stocks featured by extreme absolute strength also affects the cross-sectional variations of momentum by rebuilding the relation between firm-level attributes and momentum profits. Our study provides better understanding to academic researchers and market participants who get into the field of momentum investing.

Table 10
Enhanced momentum profits sorted by residual volatility.

	P1	P2	P3	P4	P5	Diff	FF3 Diff	FF5 Diff
Panel A: Residual IVOL obtained using characteristics								
AGE	0.409	0.834*	1.320**	0.927*	1.185**	0.776*	0.698*	0.837*
	(1.18)	(1.81)	(2.41)	(1.93)	(2.39)	(1.87)	(1.80)	(1.82)
COVERAGE	0.459	0.441	0.973**	0.828*	1.024*	0.565	0.896*	0.864
	(1.20)	(1.21)	(2.05)	(1.80)	(1.95)	(1.10)	(1.76)	(1.50)
Panel B: Residual Mom_strength obtained using characteristics								
AGE	0.469*	0.213	0.807**	0.134	0.485	0.017	0.012	−0.085
	(1.68)	(1.11)	(2.46)	(0.49)	(1.02)	(0.04)	(0.03)	(−0.20)
COVERAGE	0.486	1.057**	0.701	1.117*	1.216*	0.730	0.748	0.980**
	(1.22)	(2.10)	(1.56)	(1.95)	(1.66)	(1.52)	(1.60)	(2.05)

This table reports the enhanced JT momentum profits sorted by residual volatility measures. We first perform the cross-sectional regressions for IVOL (Panel A) or Mom_strength (Panel B) on AG or COVERAGE, and then obtain the residual characteristic from the regressions each month. For each month *t*, we conduct a dependent sorting procedure by first sorting individual stocks into quintiles by one of the residual characteristics and then into deciles by PR12. For each of the winner (loser) portfolios within each residual characteristic quintile, we remove stocks with absolute strength ranked at the top (bottom) 3% of its historical distribution. Within each quintile of the attribute (P1–P5), we calculate momentum profits as the return difference between winner and loser deciles with a 6-month holding period. We also calculate the difference in momentum profits between P5 and P1 quintiles. Numbers in the parentheses are the *t*-statistics calculated using Newey and West's (1987) robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Acknowledgment

We appreciate the helpful comments and suggestions from conference participants at the Financial Engineering Association of Taiwan (FeAT) 2019 Annual Conference (Taipei, Taiwan). We are especially indebted to an anonymous referees and Ji-Chai Lin (special issue editor) for their valuable comments that significantly enrich the content of the paper. Chaonan Lin acknowledges the financial support from the National Natural Science Foundation of China (Grant no: NSFC-71972161 and NSFC-71972162). Nien-Tzu Yang acknowledges the financial support from the Ministry of Science and Technology of Taiwan (grant number: MOST 107-2410-H-239-004-MY2).

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