Momentum returns, market states, and market dynamics: Is China different?

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Abstract

Recent studies suggest that momentum returns are conditioned by market states, but we find that China is *different*. First, we find that momentum returns in China *exclusively* follow *DOWN* markets contrary to the U.S. evidence. Second, the absence of momentum returns following UP markets in China cannot be explained by market dynamics, unlike in the U.S. Third, momentum returns in China are higher when the market continues in the same state than when it transitions to the other state as in the U.S. but this is true in China only following DOWN states.

JEL classification: G11, G12, G14

Keywords: Momentum returns; market states; market dynamics; China

I. Introduction

Cooper, Gutierrez, and Hameed (2004) report that short-run momentum returns are conditioned by market states.[1] Defining the market state as UP when the lagged three-year market return is non-negative and DOWN when it is negative, they find that momentum returns in the U.S. *exclusively* follow UP markets. In a related study, Asem and Tian (2010) show that the absence of momentum returns in the U.S. following DOWN markets is due to market dynamics. They find that momentum returns in the U.S. are higher when markets continue in the same state than when they transition to a different state to the extent that at times momentum returns are negative during market transitions. Thus, the absence of momentum returns following DOWN markets in the U.S. is the result of momentum profits generated when the market continues in the DOWN state being completely offset by the momentum losses incurred when the market transitions to the UP state.[2] Asem and Tian (2010) suggest that their findings are consistent with the behavioural model of Daniel, Hirshleifer, and Subrahmanyam (1998) but inconsistent with the competing model of Hong and Stein (1999) that predicts higher momentum returns only when the market either continues or transitions to the UP state.

Hanauer (2014) presents evidence showing that momentum returns are similarly conditioned by market states and market dynamics outside the U.S. particularly in Japan, Korea, Taiwan, and Turkey. He argues further that cross-country differences in the level of momentum returns depend on market dynamics rather than on differences in individualism as

[1] Momentum returns refer returns from a zero-investment portfolio buying past winner and selling past loser stocks.

[2] Following UP markets, the momentum profits are larger than momentum losses hence this results in net momentum returns in the U.S. Asem and Tian (2010) designate the past market state as "UP" ("DOWN") when the past 12-month return of the value-weighted Centre for Research in Security Prices Index (CRSP) is non-negative (negative). In addition, they classify the subsequent market state as "UP" ("DOWN") when the subsequent month CRSP VW return is non-negative (negative).

suggested by Chui, Titman, and Wei (2010). Hanauer (2014) suggests that unconditional momentum returns in Japan have historically been low because the positive momentum returns following market continuations have been offset by negative momentum returns following market transitions as Japan had more market transitions than the U.S.

In this paper, we examine the relation between momentum returns, market states and market dynamics in China, currently the world's largest emerging market. To the extent that momentum returns are driven by behavioural biases, the Chinese stock markets are interesting case studies as they are dominated by retail investors who are presumably more prone to behavioural biases than institutional investors (Gao, 2002). These markets are also relatively young having been established only in the early 1990s, and its investors lack the sophistication of their counterparts in the more mature developed markets, likewise making them more susceptible to irrational behaviour (Chen, Kim, Nofsinger, & Rui, 2004). Interestingly in spite of these market and investor characteristics, momentum returns in China have been historically low.

Our results suggest that China is *different* from other markets when it comes to the relation between momentum returns and market states. First, we find that China is different since momentum returns in this economy *exclusively* follow *DOWN* markets, contrary to the U.S. evidence in Cooper et al. (2004) and Asem and Tian (2010) where momentum returns exclusively follow UP markets, but still consistent to some extent with the behavioural model of Daniel et al. (1998). This can explain why unconditional momentum returns in China are historically low as the Chinese stock markets have experienced more UP than DOWN states throughout its brief history. Thus our results suggest an alternative to the "differences in individualism" explanation of low momentum returns in China as argued by Chui et al. (2010). Second, we find that the absence of momentum returns following UP markets in China cannot be explained by market dynamics, unlike the way market dynamics can explain the absence of momentum returns following DOWN markets in the U.S. Instead, we suggest that the lack of momentum returns following UP markets in China could be due to risk-seeking behaviour among Chinese investors who treat loser stocks like lottery stocks following UP markets. This makes both past winner and loser stocks equally attractive following UP markets thereby posting similar returns and negating the profitability of the momentum trading strategy. Third, though we find that momentum returns in China are higher when the market continues in the same state than when it transitions to the other state, consistent with the U.S. evidence in Asem and Tian (2010) and the non-U.S. evidence in Hanauer (2014), we find that this is true in China only following DOWN states.

We contribute to the literature in the following ways. First, as far as we are aware we are the first to document evidence that momentum returns can *exclusively* follow DOWN (not just UP) markets. Second, we confirm in the world's largest emerging market the importance of market states in conditioning momentum returns. Third, we offer an explanation for the historically low momentum returns in China that is based on market states as an alternative to the "difference in individualism" argument of Chui et al. (2010).

The rest of the paper is organised as follows. Section II provides a brief review of the literature. Section III describes our data and methods. Section IV presents the empirical results. Section V discusses potential explanation of our results. Section VI provides the robustness tests, and Section VII concludes.

II. Brief Literature Review

Behavioural explanations of the relationship between market states and momentum returns are usually based on the competing models of Daniel et al. (1998) and Hong and Stein (1999). While both models predict high momentum returns following UP markets, high momentum returns following DOWN markets is consistent only with Daniel et al. (1998).

Daniel et al. (1998) posit that investors are overconfident about the value of their private signals and overreact to them, and underreact to public signals (e.g., past market or stock returns). Further, due to biased self-attribution, confirming and disconfirming news have asymmetric effects on overconfidence. Overconfidence is heightened following the arrival of confirming news while it is dampened only slightly following the arrival of disconfirming news. Therefore, the arrival of new information would, on average, lead to an increase in overconfidence that in turn leads to further overreaction to the initial private signal, thereby causing price momentum. In this model, overconfidence can increase following both UP and DOWN markets resulting in price momentum. An investor with a "buy" trade gets a boost in confidence following a confirmatory public signal such as price appreciation during UP markets. This results in price momentum since on average investors are long following UP markets. In the same way, an investor with a "sell" trade gets a boost in confidence following a confirmatory public signal such as price depreciation during DOWN markets. This indicates that momentum returns could exist following both UP and DOWN markets, while the model also predicts higher momentum returns when markets continue in the same state either UP or DOWN than when they transition to a different state.

Though overconfidence and self-attribution bias have traditionally been regarded as universal tendencies, cultural differences in behavioural biases have been suggested in the literature, with several studies documenting that East Asians (specifically, those in Confucian cultures, such as Chinese, Koreans and Japanese) tend to be less individualistic (Hofstede, 2001), and less prone to biased self-attribution if not tending towards biased self-criticism (see, Heine & Hamamura, 2007 for an excellent review) compared with Westerners. Arguing that individualism is related to overconfidence, Chui et al. (2010) posit that cross-country differences in the level of momentum returns can be explained by differences in the level of individualism. Using Hofstede's (2001) individualism index, they find higher momentum returns for countries that score higher on the individualism index such as the U.S. and lower for countries with lower individualism index score like China. However Hanauer (2014) disputes Chui et al.'s (2010) explanation arguing instead that cross-country differences in the level of momentum returns depend on market dynamics rather than differences in individualism.

The model proposed by Hong and Stein (1999) assumes that private information diffuses gradually through time, which leads to underreaction of "news watchers" who rely *exclusively* on their private information. The resulting positive autocorrelation in prices then attracts the attention of "momentum traders" who rely exclusively on historical price information and overreact to it leading to more price continuation. Hong and Stein (1999) find that lower risk aversion leads to greater delayed overreaction that in turn leads to greater momentum returns. To the extent that UP markets lead to increased investor wealth and reduced risk aversion, they suggest that momentum returns would be higher following UP markets than following DOWN markets. They also suggest that momentum returns would be higher when markets continue in the UP state or when they transition from DOWN to UP states.

Hong and Stein's (1999) model suggest that momentum is generated by the slow diffusion of information which results in underreaction on the part of "news watchers".[3] However, in China, unlike in the U.S., reliable information on listed companies are hard to obtain hence stock prices are seldom driven by information. Instead, Kang, Liu, and Ni (2002) observe that trading practices in China suggest that the stock market is driven more by market rumors and individual investors' sentiment, than by information. In addition, several studies have documented strong herding behaviour in the Chinese stock markets (see, Tan,

[3] The positive autocorrelation in prices then attract the attention of "momentum traders" who overreact to public information. This overreaction is eventually corrected resulting to price reversals.

Chiang, Mason, & Nelling, 2008; Chiang & Zheng, 2010; Lao & Singh, 2011; Yao, Ma, & He, 2014). If the role of information in influencing investor decisions is relatively weak in China, we expect Hong and Stein's model to have weak predictive accuracy in the Chinese stock markets.

III. Data and methods

A. Data

We collect data for A-shares listed on the Shanghai and Shenzhen stock exchanges from the China Securities Market (CSMAR) from January 1995 to December 2015.[4] We exclude the period before 1995 since only a limited number of stocks were traded during that period. Following Chui et al. (2010), we set stocks with monthly returns greater (lower) than 100 (-95) percent equal to 100 (-95) percent to avoid the influence of extreme returns and any possible data recording errors.[5] At the beginning of the sample period, there were 295 stocks. At the end of the sample period, the number of stocks in the sample increased to 2085.

B. Methods

First, we calculate momentum returns based on the method proposed by Jegadeesh and Titman (1993). We use the conventional 6-month formation period for the momentum trading strategy. At the end of each month t, all stocks are ranked in ascending order on the basis of their past 6-month returns (t-6 to t-1), skipping month t to mitigate the bid-ask bounce effect. These rankings are used to form equally- and value-weighted quintile portfolios, where portfolio P1 is called the loser quintile, and portfolio P5 is the winner

[4] There are two types of shares listed in Chinese stock markets, A-shares and B-shares, accessible to the mainland Chinese residents and foreign investors, respectively. A-Shares are denominated in Chinese Yuan and B-shares are denominated in the U.S. dollars. This paper only uses A-shares since they account for almost 99.50% of the total market capitalization and B-shares are usually small stocks. We use value-weighted market returns from January 1993 to December 1995 to estimate 36-month lagged market returns.

[5] Our results remain similar if we do not set stocks with monthly returns greater (lower) than 100 (-95) percent equal to100 (-95) percent. Furthermore, our results remain similar if we delete stocks with monthly returns greater (lower) than 100 (-95) percent.

quintile. We buy (sell) the winner (loser) quintile and define the return of the momentum trading strategy as P5-P1. The portfolios are held for k holding periods (k = 3, 6, 9 and 12 months). We calculate momentum returns based on monthly rebalanced portfolios. The number of "rebalanced" portfolios in any month is equal to 1/k of the holding period months. To illustrate, the "rebalanced" momentum returns (k=6) for the month of December 2000 is based on the returns of winner minus loser quintile from the *momentum portfolio* formed at the end of November and the portfolios formed at the end of October, September, August, July, and June. This is equivalent to revising the weights of approximately 1/k of the portfolio each month and carrying over the rest from the previous months.

Furthermore, following Carhart (1997) and Fama and French (2012), we also construct Winner-minus-Loser (WML) portfolios. At the end of each month *t*, all stocks are ranked on their past 11-month returns (*t*-11 to *t*-1), skipping month *t*. We use the momentum breakpoints for 30% and 70% of lagged performance of the biggest stocks (stocks making up 90% of the aggregate market capitalisation). The loser (L) group consists of the bottom 30% of the stocks; the middle 40% as the medium (M), and the winner (W) group consists of the top 30%. Furthermore, we also independently sort stocks into two size groups using aggregate market capitalization of the top 90% of all stocks at the end of June of year *y* as the size breakpoint. The size breakpoints remain the same until the end of June of year *y*+1. Thus, the intersection of the size and WML groups results into six value-weighted portfolios: small/losers (S/L), small/medium (S/M), small/winners (S/W), big/losers (B/L), big/medium (B/M) and big/winners (B/W). The WML return is the average returns of the two winners (SW, B/W) minus the average returns of the two losers (S/L, B/L).

Inasmuch as a zero-investment momentum strategy of buying winners and short-selling losers cannot be implemented in China because of short-sale constraints, we also compare the return of winners with the market portfolio (WMMP) following Van der Hart, Slagter, and Van Dijk (2003).

We also report the CAPM and Fama-French risk-adjusted returns (alpha). To calculate risk-adjusted momentum returns for each month *t*, we regress raw momentum returns on the appropriate factors (e.g., *MKT*, *SMB*, *HML*) and a constant to obtain factor loadings (β). *MKT* is the excess return of the value-weighted market return over the one-month interest rate charged by the People's Bank of China to financial institutions. SMB is the small-minus-big premium, and HML is the high-book-to-market-minus-low-book-to-market premium.[6] The risk adjusted momentum return for each month *t* are

$$MR_{mt}^{adj} = MR_{mt} - \sum_i \beta_{im} f_{it} \tag{1}$$

where MR_{mt} is the raw momentum return from portfolio P5-P1 of month *t*, f_{it} is the realization of factor *i* in month *t*, and β_{im} is the estimated factor loading of the time-series of raw momentum returns on the risk premium and a constant.

IV. Empirical findings

A. Descriptive Statistics

Table 1 reports the descriptive statistics of the risk factors and lagged market returns from January 1996 to December 2015. The average value-weighted monthly market (RM) return is 1.55% per month, which is 1.35% higher than the risk-free (RF) rate. Consistent with Chen, Hu, Shao, and Wang (2015), we find higher and significant SMB (1% per month) premium and comparatively small and insignificant HML (0.48% per month) premium. We use lagged market returns to define UP and DOWN market states. We find more observations of UP market states when we use 36-month lagged market returns because the longer horizon generates fewer DOWN markets. For example, we find 166 UP and 74 DOWN market states

[6] Following Fama and French (1993), we generate SMB and HML factors.

for lagged 36-month market returns, 151 UP and 89 DOWN market states for lagged 24-month market returns and 128 UP and 112 DOWN market states for lagged 12-month market returns.

Table 1about here

Panel B of Table 1 reports the correlations between the risk factors and lagged market returns. The correlation between risk factors is small except for the correlation between SMB and RM which is 0.27 and statistically significant at 1% level. The correlations between RM and lagged market returns are small and insignificant. The correlations between lagged market returns and SMB and the correlations between lagged market returns and RF are positive and significant. However, the correlations between lagged market returns and HML are small and insignificant. There is a strong correlation between different measures of lagged market returns. For example, the correlations are 0.67, 0.65, and 0.43 between lagged 36- and 24-month, 24- and 12- month, and 36- and 12- month lagged market returns, respectively.

B. Momentum returns

We start by verifying the existence of momentum returns in the Chinese stock markets. Table 2 presents the average monthly equally-weighted (EW) and value-weighted (VW) momentum returns (P5-P1) and alphas as well as returns of winners (P5), and losers (P1) over the period January 1996 to December 2015 for portfolios sorted on past 6-month returns for k-month (k = 3, 6, 9, 12) holding periods.[7] Several earlier studies suggest that momentum is relatively weak in the Chinese stock markets (e.g., Van der Hart et al., 2003; Wang, 2004; Chen, Kim, Yao, & Yu, 2010; Wu, 2011; Pan, Tang, & Xu, 2013; Cheema & Nartea, 2014). Our EW and VW results are broadly consistent with these studies. The EW momentum returns range from -0.12% to 0.21% per month and VW momentum returns range

[7] The estimation period for the momentum trading strategy starts from January 1996 and ends in December 2015.

from -0.03% to 0.20% per month and statistically insignificant. All the CAPM and FF alphas are also small and statistically insignificant. It is also interesting to note that the average monthly E-W and V-W excess returns of winners over the market (WMMP) are not statistically significant. This means that given the short-sale constraints in China, a strategy of simply buying previous winners does not provide greater returns than the market portfolio.

Table 2 about here

C. Momentum returns and lagged market states

Next we examine the momentum returns conditioned on market states and report the results in Table 3. We follow Cooper et al. (2004) who employ binary UP and DOWN classifications of market states. We employ value-weighted market returns at the portfolio formation date to define the market state. If the lagged 36-month value-weighted market return is non-negative (negative), then the market state is classified as UP (DOWN). A longer horizon is expected to capture more dramatic changes in the state of the market, but this also reduces the number of observations hence this is the longest horizon used in the study. As a robustness test, we also use 24- and 12-month lagged market returns to define market states.

Table 3 about here

Table 3 shows that momentum returns in China are conditioned by market states as in the U.S. markets. Conditional momentum returns in China are higher than the unconditional momentum returns reported in Table 2. More importantly, Table 3 shows that momentum returns in China *exclusively* follow DOWN markets in sharp contrast to the findings of Cooper et al. (2004) and Asem and Tian (2010) for the U.S. markets, when we use 36- and 24-month lagged market returns.[8]

[8] Asem and Tian (2010) also report higher and significant momentum returns following UP markets, and lower and insignificant following DOWN markets when using only lagged market state.

Panel A reports the results when the market state is based on the past 36-month market returns while Panels B and C report the results when the market state is based on the past 24- and 12-month market returns. Panel A shows that for both EW and VW portfolios, momentum returns (P5-P1) *exclusively* follow DOWN markets. Following DOWN markets, the EW and VW momentum returns are both significant at 1.07% and 1.19% per month, respectively. In contrast, following UP markets the EW and VW momentum returns are both insignificant at -0.25% and -0.23% per month, respectively. The same is true with EW and VW CAPM and FF alphas. The difference in momentum returns and alpha between UP and DOWN market is large and statistically significant for both EW and VW portfolios. For example, the last column (A-B) shows that the EW (VW) momentum returns following DOWN markets are 1.33% (1.42%) per month higher than following UP markets.

Panel B shows similar patterns when we define market state based on the past 24-month market returns. EW and VW momentum returns and alpha are insignificant following UP markets but significant following DOWN markets. Most importantly, the EW (VW) momentum returns following DOWN markets are 0.70% (0.89%) per month higher than following UP markets.

Panel C shows similar patterns when we define the market state based on the past 12-month market returns. However, although EW and VW momentum returns and alpha are higher following DOWN markets than their counterparts following UP markets, they are statistically insignificant. We will come back to this in the next section.

The fact that momentum returns in China exclusively follow DOWN markets can explain why momentum returns in China have historically been low, as the Chinese stock markets experienced significantly more UP than DOWN markets from 1995 to 2015. As shown in Panel A, there are 166 UP compared with 74 DOWN states when market states are defined based on the previous 36-month market returns, while there are 151 (128) UP and 89

(112) DOWN states when market states are defined based on the previous 24-month (12-month) market returns as shown in Panel B (C).

D. Momentum returns and market dynamics

In this section, we examine the relationship between momentum returns and market dynamics. According to the overconfidence model of Daniel et al. (1998), momentum returns should be higher when the market continues in the same state (UP/UP or DN/DN) than when it transitions to a different state (UP/DN or DN/UP). On the other hand, Hong and Stein's (1999) gradual diffusion model suggests that momentum returns would be higher when the market continues in the UP state or when it transitions from DOWN to UP states.

Asem and Tian (2010) classify market states based on lagged and contemporaneous market returns and show higher and significant momentum returns when lagged and contemporaneous market returns are either both negative or both non-negative, consistent with the overconfidence model of Daniel et al. (1998). Following Asem and Tian (2010) we also classify market states based on lagged and contemporaneous market returns. Lagged market returns are defined as past 12-month (*t*-11 to *t*) returns while contemporaneous market returns are from month *t*+1. Table 4 reports momentum returns and alphas following 12-month lagged market returns.[9] Similar to the results reported in Table 3 we find insignificant momentum returns and alphas following UP markets regardless of the contemporaneous market state. Momentum returns and alphas are both insignificant whether the lagged/contemporaneous market is UP/UP or UP/DN unlike in Asem and Tian (2010) who find higher momentum returns when lagged and contemporaneous markets are both UP. Therefore, the absence of momentum returns following UP markets in China is *not* due to market dynamics. If it were, we should find offsetting momentum gains and losses from

[9] We conduct the analysis for k holding periods (k= 3, 6, 9, and 12 months). To save space we only report the results for the 6-month holding period. The results for other holding periods are similar to the results we report here. These are available upon request.

UP/UP and UP/DN market states respectively, instead of being both insignificant as shown by our results. In fact, the difference in momentum returns (A-B) between market continuation in the UP state (UP/UP) and transition to the DN state (UP/DN) is small (-0.40% per month) and statistically insignificant.

Table 4 about here

Furthermore, we find positive and significant momentum returns and alphas only when the market continues in the DOWN state (DN/DN). In contrast, we find negative but statistically insignificant momentum returns and alphas when the market transitions to the UP state (DN/UP). To illustrate, momentum return (CAPM alpha) is 1.32% (1.19%) per month in DN/DN market state while it is -0.52% (-0.35%) per month in the DN/UP market state. Furthermore, the last column of Table 4 shows that momentum returns (CAPM alpha) when the market continues in the DN state are 1.83% (1.54%) per month higher than when market transitions to the UP state.

Recall from Panel C of Table 3 that we reported comparatively small momentum returns following DOWN markets compared to the Panels A and B. Our results from Table 4 show that the small momentum returns in Panel C of Table 3 are due to market dynamics as higher momentum returns in DN/DN state are offset to some extent by momentum losses in DN/UP state. Our results are consistent with Asem and Tian's (2010) suggestion that momentum returns are higher when the market continues in the same state than when they transition to a different state *but* only when the market continues in the DOWN state.

V. Potential Explanations

Our results suggest that China is different because we find that momentum returns *exclusively* follow DOWN and not UP markets as in the U.S. Therefore our results are more consistent with Daniel et al.'s model but not with Hong and Stein's which predicts high momentum returns only following UP markets. Furthermore, the absence of momentum returns following UP markets in China cannot be explained by market dynamics unlike the absence of momentum returns in the U.S. following DOWN markets. The low unconditional momentum returns in China are likely caused by a combination of market states, i.e., more UP than DOWN states, and market dynamics, i.e., since even in DOWN states, momentum returns when the market continues DOWN are partially offset by momentum losses when the market transitions UP leading to relatively low though positive momentum returns following DOWN markets.

The presence of momentum returns when the market continues in the DOWN state (DN/DN) is consistent with the Daniel et al. (1998) model which predicts higher momentum returns when markets continue in the same state than when it transitions to a different state, but only to the extent that investors underreact to public signals because short-sale restrictions make it difficult to trade based on the confirming information after a sale. In the Daniel et al. (1998) model, investors simultaneously overreact to the private information and underreact to the public signals. Therefore, in the presence of the short sale restrictions, investors could only underreact to the public information but not overreact to the private information following DOWN market states which result in the positive autocorrelation of prices or momentum in DN/DN state.

The presence of momentum returns following DOWN markets is also consistent with Du's (2002) "hesitation model". Du's (2002) model presumes the presence of heterogeneous investors with differing levels of overconfidence. In this model, momentum is attributed to the hesitation of low confidence investors from immediately trading following the release of firm-specific news thereby generating underreaction. To the extent that low confidence investors exhibit stronger hesitation following DOWN markets having just incurred losses, the underreaction is expected to be stronger hence leading to higher momentum returns.

So why do we not observe momentum returns in China following UP markets where recent past losers (LSRs) post returns very similar those of recent past winners (WNRs)? We suggest that this is due to the risk-seeking behaviour of individual Chinese investors who are attracted to LSR stocks following UP markets because of their lottery-like characteristics. Kumar (2009) defines lottery-type stocks as those with a low price, high idiosyncratic volatility and high idiosyncratic skewness. Recent losers would presumably have a low price. Kumar also reports that lottery-type stocks tend to be small stocks with very low market capitalisation. In addition, Kausar, Kumar, and Taffler (2013) report that firms that have had significant financial problems and are poor performing also exhibit lottery-type characteristics. Hence we suggest that recent losers especially small loser stocks would presumably have lottery-like characteristics. The suggestion that risk-seeking Chinese retail investors are attracted to lottery-like stocks following UP markets is consistent with Fong (2013) who find that risk-seekers prefer lottery stocks in periods of high sentiment and Fong and Toh (2014) who find that overoptimistic investors exhibit a preference for lottery-type stocks. Indeed, there is ample evidence in the psychology and finance literature suggesting a predisposition among Chinese to exhibit risk-seeking or gambling behaviour. The psychology literature suggests the acceptability of gambling as a form of social activity in Chinese communities (Raylu & Oei, 2004), to such an extent that social gambling is the preferred form of entertainment (Loo, Raylu, & Oei, 2008). The finance literature also supports such a predisposition. Ma (1996) reports evidence of risk-seeking behaviour among mainland Chinese investors by establishing a positive relationship between share prices and domestic beta risk. Ng and Wu (2006) analyze a comprehensive 64.22 million trades of 6.8 million institutional and individual investors in mainland China and report that Chinese investors tend to prefer stocks with large betas and high idiosyncratic risk. Lee and Wong (2012) also find that Chinese investors tend to trade more heavily on riskier stocks based on panel data drawn from the Shanghai stock market. This is supported by Fong, Wong, and Yong (2010) who find evidence that mainland Chinese investors are more speculative and have higher risk appetites than Hong Kong and international investors. Therefore, though WNRs are naturally attractive following UP markets, we suggest that the predisposition to gamble among Chinese individual investors results in LSRs becoming equally attractive.

In Table 5 we report the average monthly return of loser and winner stocks of small and big size portfolios, and WML momentum returns. The average monthly returns of small size portfolios (SL, SW) are higher than big size portfolios (BL, BW) when the market continues in the UP state (UP/UP). Most importantly, the average monthly return of SL is higher than SW portfolio, supporting to a degree the suggestion that small size stocks especially LSRs exhibit lottery-like characteristics. Results in Table 5 also provide evidence that our findings in Table 4 survive even when we use a different method to calculate momentum returns.

Table 5 about here

In sum, we posit that risk-seeking individual Chinese investors become overoptimistic following UP markets, hence the preference for lottery stocks in the guise of LSR stocks. In such an environment, both WNR and LSR stocks post similar returns, thereby eliminating the profitability of the momentum trading strategy. We would even go so far to suggest that following UP markets, LSRs become so attractive to Chinese investors that they could even be switching to some degree, from WNRs to LSRs, consistent with a predisposition to gamble. There is evidence consistent with this in Table 4 which shows that though WNRs continue winning, their 6-month holding period returns are lower than the 6-month formation period returns. Interestingly for LSRs, instead of continuing to lose, they start to rebound posting 6-month holding period returns similar in magnitude to those of WNRs in the UP/UP state. For example, in the UP/UP market state the holding period return of WNRs (P5) at 8.76% is lower than their formation period return at 15.48%. The same holds in the UP/DN market states with the holding period return of WNRs (P5) at -5.43% being lower than their formation period return at 14.68%. On the other hand the holding period return of LSRs (P1) in the UP/UP market states at 9.01% is higher than their formation period return at -1.41%. However, the holding period return of LSRs (P1) at -5.59% is lower than their formation period return at -1.94%, but the reduction is not equal to the reduction of the holding period return of WNRs (P5) from 14.68% of the formation period to -5.43% of the holding period.

But why don't we observe this (equal returns of WNRs and LSRs following UP markets) in other markets such as the U.S.? We suggest that this is because other markets are not as dominated by individual investors who have strong risk-seeking behaviour.

Following DOWN markets, we document momentum returns since the attraction towards lottery stocks (e.g., LSRs) is not as intense following UP markets consistent with the argument in Fong (2013) and Fong and Toh (2014), so LSRs do not earn as much. In fact LSRs continue losing, and while WNRs also lose, they do not lose as much, giving rise to momentum returns.

VI. Robustness Tests

A. Market state as a continuous variable

So far, we have treated market states as binary UP and DOWN states. As a robustness test, we also examine the relation between momentum returns and market states by treating the latter as a continuous variable. Market state is thus defined by the lagged market return itself. We regress raw and risk-adjusted (CAPM and Fama-French) momentum returns against the 36-month lagged market returns and the square of the lagged market returns to test for non-linearity. Panel A of Table 6 shows that raw and risk-adjusted (CAPM) momentum returns are negatively related to lagged market returns and are statistically significant.[10] This is further confirmation that momentum returns in China are higher following DOWN (not UP) markets. The coefficient of the square of lagged market returns is

[10] Risk-adjusted (CAPM) momentum returns are significant at 10% level.

not statistically significant which implies a linear relationship between market states and momentum returns.

Table 6 about here

In Panel B of Table 6, we allocate raw and risk-adjusted (CAPM and Fama-French) momentum returns into quintiles based on the 36-month lagged market returns and report mean monthly momentum returns for each quintile. We find large and significant raw and risk-adjusted (CAPM) momentum returns when lagged market returns are lowest (DOWN) and reverse but insignificant raw and risk-adjusted (CAPM) momentum returns when lagged market returns are highest (UP). This is yet additional confirmation that momentum returns in China are higher following DOWN (not UP) market states.

B. Market turnover and momentum returns

In this section, we condition momentum returns on market turnover (TURN) since Statman, Thorley, and Vorkink (2006) and Gervais and Odean (2001) find that TURN is positively related to lagged market returns. In the previous section, we find higher momentum returns following DOWN markets. Therefore, we expect higher momentum returns following low TURN if it is positively related to lagged market returns.

Table 7 about here

We divide our sample into two periods, high and low TURN. We define TURN at the portfolio formation date based on the ratio of volume of shares to the outstanding shares in the past 12 months.[11] Consistent with our expectation, we find higher and significant momentum returns only following low TURN periods. For example, we find momentum returns of 0.84% (0.85%) per month following low TURN periods. In contrast, we find negative but insignificant momentum returns and alpha following high TURN periods.

[11] Our results are similar even when we use past 6- or 1-month turnover to define high and low turnover periods. Furthermore, our results are similar when we use the median turnover to define high and low turnover periods.

Furthermore, we find that momentum returns (CAPM alpha) are 1.30% (1.27%) per month higher following low than high TURN periods. In sum, these results further provide evidence that momentum returns in China are higher following DOWN market states.

C. Momentum returns and market dynamics (Excluding 2007 and 2015 periods)

The Chinese stock markets experienced two peaks, one in 2007 and another in 2015. In this section, we examine the impact of market dynamics on momentum returns once we exclude these two years from our sample.[12]

Table 8 about here

We define lagged and subsequent market states similar to that in section IV.D and report results in Table 8. The exclusion of the peak periods decreases the UP/UP market states from 77 to 60 and UP/DN from 51 to 44 months. As expected, it does not affect the DN/DN and DN/UP months since 2007 and 2015 are peak periods of market performance. Furthermore, the exclusion of the peak periods also decreases the average value-weighted monthly market returns and holding period returns of both loser and winner portfolios by approximately 2% per month in the UP/UP market state. However, the exclusion of peak periods does not affect momentum returns in the UP/UP and UP/DN market states, so our results in Table 8 are similar to our main results in Table 4.

VII. Conclusion

Recent studies suggest that momentum returns are conditioned by market states with Cooper et al. (2004) reporting that momentum returns in the U.S. *exclusively* follow *UP* markets. The absence of momentum returns in the U.S. following DOWN markets is explained by Asem and Tian (2010) as the result of market dynamics wherein momentum

[12] We are thankful to the reviewer for pointing out about the peak periods in the Chinese Stock markets. We also examine the impact of the exclusion of peak periods on the relation between momentum returns and lagged market states. The results remain similar to those reported in Table 3.

returns experienced when the market continues in the DOWN state are offset by momentum losses when the market reverses to the UP state.

Though we find that momentum returns in China are also conditioned by market states, our results suggest that China is *different*. First, we find that momentum returns in China *exclusively* follow *DOWN* markets unlike in the U.S. Our results can explain why momentum returns in China have been historically low as it has experienced more UP than DOWN market states. Second, we find that the absence of momentum returns following UP markets in China cannot be explained by market dynamics, unlike the way it does in explaining the absence of momentum returns following DOWN markets in the U.S. Instead, we suggest that the absence of momentum returns following UP markets in China could be due to the risk-seeking behaviour of Chinese individual investors who find lottery-like past loser stocks equally attractive as past winner stocks following UP markets. In such an environment, both past winner and loser stocks post similar returns, negating the profitability of the momentum trading strategy. Third, though we find consistent with the U.S. and the non-U.S. evidence that the momentum returns in China are higher when the market continues in the same state than when it transitions to the other state, this is true in China only following DOWN states.

We contribute to the literature in the following ways. First, we document evidence that momentum returns can *exclusively* follow DOWN (not just UP) markets. Second, we confirm the importance of market states in conditioning momentum returns in the world's largest emerging market. Third, we offer an alternative explanation for the historically low momentum returns in China based on market states instead of the low level of individualism as suggested by Chui et al. (2010).

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References

Asem, E., & Tian, G. Y. (2010). Market dynamics and momentum profits. *Journal of Financial and Quantitative Analysis, 45*, 1549-1562.

Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of Finance, 52*, 57-82.

Cheema, M. A., & Nartea, G. V. (2014). Momentum returns and information uncertainty: Evidence from China. *Pacific-Basin Finance Journal, 30*, 173-188.

Chen, C., Hu, X., Shao, Y., & Wang, J. (2015). Fama-French in China: Size and Value Factors in Chinese Stock Returns. *University of Hong Kong Working Paper*.

Chen, G.-M., Kim, K. A., Nofsinger, J. R., & Rui, O. M. (2004). Behavior and performance of emerging market investors: Evidence from China. *unpublished Washington State University Working paper (January)*.

Chen, X., Kim, K. A., Yao, T., & Yu, T. (2010). On the predictability of Chinese stock returns. *Pacific-Basin Finance Journal*, *18*, 403-425.

Chiang, T. C., & Zheng, D. (2010). An empirical analysis of herd behavior in global stock markets. *Journal of Banking & Finance, 34*, 1911-1921.

Chui, A. C., Titman, S., & Wei, K. J. (2010). Individualism and momentum around the world. *The Journal of Finance, 65*, 361-392.

Cooper, M. J., Gutierrez, R. C., & Hameed, A. (2004). Market states and momentum. *The Journal of Finance, 59*, 1345-1365.

Daniel, K. D., Hirshleifer, D., & Subrahmanyam, A. (1998). Investor psychology and security market under- and overreactions. *The Journal of Finance, 53*, 1839-1885.

Du, J. (2002). Heterogeneity in investor confidence and asset market under-and overreaction. *Available at SSRN 302684*.

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics, 33*, 3-56.

Fama, E. F., & French, K. R. (2012). Size, value, and momentum in international stock returns. *Journal of Financial Economics, 105*, 457-472.

Fong, T., Wong, A., & Yong, I. (2010). Share price disparity in Chinese stock markets. *Journal of Financial Transformation, 30*, 23-31.

Fong, W. M. (2013). Risk preferences, investor sentiment and lottery stocks: A stochastic dominance approach. *Journal of Behavioral Finance, 14*, 42-52.

Fong, W. M., & Toh, B. (2014). Investor sentiment and the MAX effect. *Journal of Banking & Finance, 46*, 190-201.

Gao, S. (2002). China stock market in a global perspective. *Dow Jones Indexes*, 1-48.

Gervais, S., & Odean, T. (2001). Learning to be overconfident. *Review of Financial Studies, 14*, 1-27.

Hanauer, M. (2014). Is Japan Different? Evidence on Momentum and Market Dynamics. *International Review of Finance, 14*, 141-160.

Heine, S. J., & Hamamura, T. (2007). In search of East Asian self-enhancement. *Personality and Social Psychology Review, 11*, 4-27.

Hofstede, G. H. (2001). *Culture's consequences: Comparing values, behaviors, institutions and organizations across nations*: Sage.

Hong, H., & Stein, J. C. (1999). A unified theory of underreaction, momentum trading, and overreaction in asset markets. *The Journal of Finance, 54*, 2143-2184.

Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of Finance, 48*, 65-91.

Kang, J., Liu, M.-H., & Ni, S. X. (2002). Contrarian and momentum strategies in the China stock market: 1993–2000. *Pacific-Basin Finance Journal*, *10*, 243-265.

Kausar, A., Kumar, A., & Taffler, R. (2013). Why the going-concern anomaly: gambling in the market? *Available at SSRN:* http://dx.doi.org/10.2139/ssrn.2249029.

Kumar, A. (2009). Who gambles in the stock market? *The Journal of Finance*, *64*, 1889-1933.

Lao, P., & Singh, H. (2011). Herding behaviour in the Chinese and Indian stock markets. *Journal of Asian Economics*, *22*, 495-506.

Lee, J. K.-Y., & Wong, A. Y.-T. (2012). Impact of financial liberalisation on stock market liquidity: experience of China. *Journal of Chinese Economic and Foreign Trade Studies, 5*, 4-19.

Loo, J. M., Raylu, N., & Oei, T. P. S. (2008). Gambling among the Chinese: A comprehensive review. *Clinical Psychology Review, 28*, 1152-1166.

Ma, X. (1996). Capital controls, market segmentation and stock prices: Evidence from the Chinese stock market. *Pacific-Basin Finance Journal, 4*, 219-239.

Ng, L., & Wu, F. (2006). Revealed stock preferences of individual investors: Evidence from Chinese equity markets. *Pacific-Basin Finance Journal, 14*, 175-192.

Pan, L., Tang, Y., & Xu, J. (2013). Weekly momentum by return interval ranking. *Pacific-Basin Finance Journal, 21*, 1191-1208.

Raylu, N., & Oei, T. P. (2004). Role of culture in gambling and problem gambling. *Clinical Psychology Review, 23*, 1087-1114.

Statman, M., Thorley, S., & Vorkink, K. (2006). Investor overconfidence and trading volume. *Review of Financial Studies, 19*, 1531-1565.

Tan, L., Chiang, T. C., Mason, J. R., & Nelling, E. (2008). Herding behavior in Chinese stock markets: An examination of A and B shares. *Pacific-Basin Finance Journal, 16,* 61-77.

Van der Hart, J., Slagter, E., & Van Dijk, D. (2003). Stock selection strategies in emerging markets. *Journal of Empirical Finance, 10,* 105-132.

Wang, C. (2004). Relative strength strategies in China's stock market: 1994–2000. *Pacific-Basin Finance Journal, 12*, 159-177.

Wu, Y. (2011). Momentum trading, mean reversal and overreaction in Chinese stock market. *Review of Quantitative Finance and Accounting, 37,* 301-323.

Yao, J., Ma, C., & He, W. P. (2014). Investor herding behaviour of Chinese stock market. *International Review of Economics & Finance, 29,* 12-29.

Table 1: Descriptive statistics

This table reports the summary statistics of monthly average value-weighted market returns (RM), the risk-free rate (RF), small-minus-big size factor (SMB), the high-minus-low book to market factor (HML), and lag 36-, 24- and 12-month value-weighted market returns. UP (DOWN) represents the number of non-negative (negative) Value-Weighted Market Returns over months *t*-m (m=36, 24, 12). The summary statistics are computed over the holding period of momentum strategy from January 1996 to December 2015. All the variables in Panel A are reported in percent.

Panel A. Summary statistics								
Variable	N	UP	DOWN	Mean	Std Dev	Median	Maximum	Minimum
RM	240	-	-	1.55	9.09	1.33	36.34	-26.51
RF	240	-	-	0.20	0.07	0.17	0.56	0.09
SMB	240	-	-	1.00	5.19	1.00	19.99	-19.79
HML	240	-	-	0.48	4.33	0.29	28.18	-15.69
LAG36	240	166	74	62.36	106.60	36.780	451.26	-62.67
LAG24	240	151	89	49.86	110.24	13.340	552.92	-41.38
LAG12	240	128	112	25.07	61.22	5.540	273.22	-68.76

Panel B. Correlation							
Variable	RM	RF	SMB	HML	LAG36	LAG24	LAG12
RM	1						
RF	-0.01	1					
SMB	0.27	0.02	1				
HML	0.08	0.08	-0.18	1			
LAG36	0.00	0.31	0.22	-0.04	1		
LAG24	0.02	0.46	0.20	0.00	0.67	1	
LAG12	0.12	0.21	0.17	-0.03	0.43	0.65	1

Table 2: Equally-weighted and value-weighted momentum returns

At the end of each month *t*, all stocks are allocated into quintiles based on their lagged 6-month (*t*-6 to *t*-1) returns, skipping month *t*. We then form an equal-weighted and value-weighted zero-cost portfolio selling (buying) the quintile of stocks with the lowest (highest) 6-month lagged returns. Portfolios are held for 3, 6, 9 and 12 months. Following Jegadeesh and Titman (1993), portfolios are rebalanced monthly. Monthly average returns of P1 (Loser), P5 (Winner), P5-P1 (momentum returns), MP (market portfolio), WMMP (winner minus market portfolio) and CAPM and Fama-French alphas over the sample period are reported below. All the returns are reported in percent and their *t*-statistics provided in parentheses. The sample period is from January 1995 to December 2015.

Panel A: Equally-weighted momentum returns

K=	**3**	**6**	**9**	**12**
P1 (Losers)	1.92	2.00	1.97	1.94
	(2.88)	(2.96)	(2.92)	(2.88)
P5 (Winners)	2.13	2.15	1.97	1.82
	(3.25)	(3.30)	(3.06)	(2.83)
P5-P1	0.21	0.15	0.00	-0.12
	(0.79)	(0.64)	(-0.01)	(-0.61)
MP	2.22	2.22	2.22	2.22
	(3.41)	(3.41)	(3.41)	(3.41)
WMMP	-0.10	-0.10	-0.16	-0.21
	(-0.62)	(-0.73)	(-1.26)	(-1.90)
CAPM-ALPHA	0.24	0.18	0.03	-0.10
	(0.92)	(0.78)	(0.12)	(-0.48)
FF-ALPHA	0.43	0.37	0.22	0.11
	(1.69)	(1.65)	(1.08)	(0.58)

Panel B: Value-weighted momentum returns

K=	**3**	**6**	**9**	**12**
P1 (Losers)	1.40	1.33	1.29	1.25
	(2.26)	(2.18)	(2.14)	(2.1)
P5 (Winners)	1.41	1.53	1.40	1.22
	(2.41)	(2.57)	(2.39)	(2.11)
P5-P1	0.01	0.20	0.12	-0.03
	(0.04)	(0.70)	(0.46)	(-0.12)
MP	1.55	1.55	1.55	1.55
	(2.65)	(2.65)	(2.65)	(2.65)
WMMP	-0.14	-0.04	-0.03	-0.07
	(-0.71)	(-0.24)	(-0.18)	(-0.45)
CAPM-ALPHA	0.06	0.25	0.16	0.01
	(0.18)	(0.86)	(0.63)	(0.04)
FF-ALPHA	0.27	0.45	0.37	0.23
	(0.82)	(1.63)	(1.56)	(1.06)

Table 3: Momentum returns and market states

At the end of each month *t*, all stocks are allocated into quintiles based on their lagged 6-month (*t*-6 to *t*-1) returns, skipping month *t*. These portfolios are held for six months (*t*+1 to *t*+6). Following Jegadeesh and Titman (1993), portfolios are rebalanced monthly. Non-negative (negative) Value-Weighted Market Returns over past 36-, 24-, and 12-months are used to define UP (DOWN) market states. Monthly average returns of P1 (Loser), P5 (Winner), P5-P1 (momentum returns), MP (market portfolio), WMMP (winner minus market portfolio) and CAPM and Fama-French alphas over the sample period are reported below. Panels A, B, and C report momentum returns following 36-, 24-, and 12-month lagged market returns, respectively. A-B represents the difference in momentum returns between UP and DOWN markets. All the returns are reported in percent and their *t*-statistics provided in parentheses. The sample period is from January 1995 to December 2015.

Panel A: Momentum returns following 36-month UP and DOWN markets

	E-W			V-W		
	UP(A)	DOWN(B)	A-B	UP(A)	DOWN(B)	A-B
N	166	74		166	74	
P1 (Losers)	2.51	0.82		1.67	0.55	
	(2.96)	(0.77)		(2.15)	(0.59)	
P5 (Winners)	2.26	1.89		1.44	1.74	
	(2.65)	(2.15)		(1.82)	(2.25)	
P5-P1	-0.25	1.07	-1.33	-0.23	1.19	-1.42
	(-1.01)	(2.11)	(-2.62)	(-0.71)	(2.17)	(-2.30)
MP	2.58	1.41		1.72	1.17	
	(3.07)	(1.49)		(2.26)	(1.41)	
WMMP	-0.36	0.49		-0.32	0.57	
	(-2.31)	(1.75)		(-1.49)	(1.71)	
CAPM-ALPHA	-0.22	1.10	-1.31	-0.18	1.22	-1.40
	(-0.86)	(2.18)	(-2.60)	(-0.55)	(2.27)	(-2.28)
FF-ALPHA	0.05	1.12	-1.07	0.10	1.26	-1.16
	(0.18)	(2.40)	(-2.20)	(0.30)	(2.51)	(-1.99)

Panel B: Momentum returns following 24-month UP and DOWN markets

	E-W			V-W		
	UP(A)	DOWN(B)	A-B	UP(A)	DOWN(B)	A-B
N	151	89		151	89	
P1 (Losers)	2.68	0.80		1.78	0.54	
	(2.93)	(0.85)		(2.12)	(0.66)	
P5 (Winners)	2.58	1.39		1.66	1.30	
	(2.81)	(1.77)		(1.97)	(1.80)	
P5-P1	-0.10	0.60	-0.70	-0.12	0.76	-0.89
	(-0.36)	(1.72)	(-1.76)	(-0.33)	(1.74)	(-1.74)
MP	2.90	1.12		2.03	0.73	
	(3.20)	(1.33)		(2.44)	(1.04)	
WMMP	-0.32	0.27		-0.37	0.52	
	(-1.83)	(1.17)		(-1.53)	(2.05)	
CAPM-ALPHA	-0.06	0.61	-0.67	-0.06	0.78	-0.84
	(-0.20)	(1.76)	(-1.68)	(-0.16)	(1.81)	(-1.62)
FF-ALPHA	0.22	0.64	-0.42	0.24	0.82	-0.58
	(0.77)	(1.79)	(-1.33)	(0.65)	(2.07)	(-1.21)

Table 3: Continued

Panel C: Momentum returns following 12-month UP and DOWN markets						
	E-W			V-W		
	UP(A)	DOWN(B)	A-B	UP(A)	DOWN(B)	A-B
N	128	112		128	112	
P1 (Losers)	3.19	0.62		2.09	0.46	
	(3.51)	(0.62)		(2.56)	(0.50)	
P5 (Winners)	3.11	1.04		2.18	0.78	
	(3.42)	(1.13)		(2.61)	(0.93)	
P5-P1	-0.09	0.43	-0.51	0.09	0.33	-0.24
	(-0.27)	(1.41)	(-1.08)	(0.24)	(0.93)	(-0.51)
MP	3.43	0.89		2.37	0.62	
	(3.82)	(0.94)		(2.91)	(0.89)	
WMMP	-0.33	0.16		-0.20	0.13	
	(-1.67)	(0.79)		(-0.84)	(0.45)	
CAPM-ALPHA	-0.03	0.44	-0.47	0.16	0.34	-0.18
	(-0.11)	(1.56)	(-1.40)	(0.43)	(0.78)	(-0.31)
FF-ALPHA	0.29	0.47	-0.19	0.50	0.39	0.11
	(0.91)	(1.63)	(-0.61)	(1.36)	(0.94)	(0.20)

Table 4: Momentum returns, lagged and contemporaneous market states

At the end of each month *t*, all stocks are allocated into quintiles based on their lagged 6-month (*t*-6 to *t*-1) returns, skipping month *t*. These portfolios are held for six months (*t*+1 to *t*+6). Following Jegadeesh and Titman (1993), portfolios are rebalanced monthly. Non-negative (negative) Value-Weighted Market Returns over months *t*-11 to *t* and value-weighted contemporaneous market returns over the month of *t*+1 are used to define UP/UP, UP/DN, DN/UP and DN/DN market states. If lagged market returns and contemporaneous market returns are non-negative (negative), market state is UP/UP (DN/DN). If lagged market returns are non-negative (negative), and contemporaneous market returns are negative (non-negative), then the market state is defined as UP/DN (DN/UP). Monthly average returns of P1 (Loser), P5 (Winner), P5-P1 (momentum returns), MP (market portfolio), WMMP (winner minus market portfolio) and CAPM and Fama-French alphas over the sample period are reported below. A-B represents the difference in momentum returns between UP/UP and UP/DN markets, while C-D represents the difference in momentum returns between DN/UP and DN/DN markets. All the returns are reported in percent and their *t*-statistics provided in parentheses. The sample period is from January 1995 to December 2015.

Momentum returns following 12-month and contemporaneous market returns						
	UP/UP(A)	UP/DN(B)	A-B	DN/UP(C)	DN/DN(D)	C-D
N	77	51		54	58	
Loser (Formation)	-1.41	-1.94		-5.15	-4.63	
	(-5.08)	(-5.41)		(-18.44)	(-25.27)	
Winner (Formation)	15.48	14.68		5.38	4.75	
	(17.95)	(13.78)		(10.00)	(12.94)	
P1 (Holding)	9.01	-5.59		8.31	-6.67	
	(9.84)	(-6.33)		(7.40)	(-7.95)	
P5 (Holding)	8.76	-5.43		7.79	-5.35	
	(9.24)	(-6.18)		(7.92)	(-5.71)	
P5-P1	-0.25	0.15	-0.40	-0.52	1.32	-1.83
	(-0.55)	(0.36)	(-0.64)	(-1.02)	(2.83)	(-2.83)
MP	9.20	-5.27		8.13	-5.94	
	(10.02)	(-6.33)		(7.86)	(-7.27)	
WMMP	-0.43	-0.17		-0.33	0.62	
	(-1.57)	(-0.63)		(-1.22)	(2.30)	
CAPM-ALPHA	-0.06	0.00	-0.06	-0.35	1.19	-1.54
	(-0.13)	(0.01)	(-0.11)	(-0.70)	(2.52)	(-2.41)
FF-ALPHA	0.26	0.32	-0.06	-0.30	1.21	-1.51
	(0.57)	(0.87)	(-0.10)	(-0.67)	(2.61)	(-2.27)

Table 5: WML momentum returns, lagged and contemporaneous market states

At the end of each month *t*, all stocks are allocated into three groups based on their returns from month *t*-11 to *t*-1: losers (L) as bottom 30%, medium (M) as 40% and winners as top 30%. The stocks are also allocated into two groups based on their market capitalization of month *t*, bottom 90% as small (S) and top 10% big (B). The sorting on past returns and size result into six portfolios: S/L, S/M, S/B, B/L, B/M and B/W. We calculate the value-weighted returns of these portfolios for month *t*+1, skipping month *t* to mitigate bid-ask bounce effect. WML equals the average monthly returns of the two winners portfolios (S/W and B/W) minus the average returns of the two losers (S/L and B/L) portfolios. Non-negative (negative) Value-Weighted Market Returns over months *t*-11 to *t* and value-weighted contemporaneous market returns over the month of *t*+1 are used to define UP/UP, UP/DN, DN/UP and DN/DN market states. If lagged market returns and contemporaneous market returns are non-negative (negative), market state is UP/UP (DN/DN). If lagged market returns are non-negative (negative), and contemporaneous market returns are negative (non-negative), then the market state is defined as UP/DN (DN/UP). Monthly average returns of small loser (SL) and winner (SB), big loser (BL) and winner (BW), loser (L) and winner (W), momentum returns (WML), MP (market portfolio), WMMP (winner minus market portfolio), and CAPM and Fama-French alphas over the sample period are reported below. A-B represents the difference in momentum returns between UP/UP and UP/DN markets, while C-D represents the difference in momentum returns between DN/UP and DN/DN markets. All the returns are reported in percent and their *t*-statistics provided in parentheses. The sample period is from January 1995 to December 2015.

WML momentum returns following lagged 12-month and contemporaneous (*t*+1) market returns						
	UP/UP(A)	UP/DN(B)	A-B	DN/UP(C)	DN/DN(D)	C-D
N	77	51		54	58	
SL	11.57	-2.74		10.09	-5.87	
	(9.80)	(-2.67)		(7.35)	(-5.89)	
SW	10.19	-3.64		9.10	-4.99	
	(7.85)	(-2.68)		(6.95)	(-4.50)	
BL	7.97	-6.36		7.40	-6.59	
	(10.96)	(-8.84)		(7.07)	(-8.36)	
BW	7.35	-6.39		6.58	-4.72	
	(9.18)	(-7.35)		(6.85)	(-7.13)	
L	9.77	-4.55		8.74	-6.23	
	(11.42)	(-5.55)		(7.64)	(-7.28)	
W	8.77	-5.02		7.84	-4.85	
	(9.68)	(-5.22)		(7.90)	(-6.02)	
WML	-1.00	-0.47	-0.53	-0.91	1.37	-2.28
	(-1.45)	(-0.66)	(-0.54)	(-1.61)	(3.42)	(-3.33)
MP	9.20	-5.27		8.13	-5.97	
	(10.02)	(-6.33)		(7.86)	(-7.18)	
WMMP	-0.01	-0.12		-0.29	1.12	
	(-0.03)	(-0.24)		(-0.85)	(4.86)	
CAPM-ALPHA	-0.82	-0.62	-0.20	-0.74	1.24	-1.98
	(-1.18)	(-0.87)	(-0.21)	(-1.33)	(3.09)	(-2.91)
FF-ALPHA	-0.50	-0.30	-0.20	-0.69	1.26	-1.96
	(-0.72)	(-0.43)	(-0.20)	(-1.36)	(3.20)	(-3.03)

Table 6: Lagged market returns as a continuous measure of the state of the market

At the end of each month *t*, all stocks are allocated into quintiles based on their lagged 6-month (*t*-6 to *t*-1) returns, skipping month *t*. These portfolios are held for six months (*t*+1 to *t*+6). Following Jegadeesh and Titman (1993), portfolios are rebalanced monthly. These momentum returns are regressed against an intercept, lagged market return (LAGMKT), and lagged market return squared (LAGMKT^2). Panel A provides the monthly regression coefficients and *t*-statistics following 36-month lagged market returns. In Panel B, momentum portfolios (winner minus loser quintiles) are sorted into quintiles (5-portfolios) based on the full sample of lagged 36-month market returns. Average monthly momentum returns are reported in percent along with their *t*-statistics provided in parentheses. Quintile DOWN shows momentum returns for the lowest lagged market return quintile and quintile UP for the highest lagged market return quintile. The sample period is from January 1995 to December 2015.

Panel A: 36-month lagged market

	Intercept	LAGMKT	LAGMKT^2	Adj-R2
Raw Momentum	0.70	-1.05	-0.05	0.04
	(2.38)	(-1.83)	(-0.10)	
CAPM alpha	0.74	-0.95	-0.15	0.04
	(2.54)	(-1.69)	(-0.27)	
Fama-French Alpha	0.81	-0.59	-0.24	0.02
	(2.88)	(-1.23)	(-0.45)	

Panel B: Momentum returns by quintiles of lagged 36-month market returns

	DOWN	2	3	4	UP
Raw Momentum	1.20	0.63	0.24	-0.68	-0.62
	(1.92)	(1.30)	(0.43)	(-1.68)	(-1.33)
CAPM alpha	1.21	0.66	0.29	-0.59	-0.64
	(1.96)	(1.38)	(0.52)	(-1.46)	(-1.37)
Fama-French Alpha	1.12	0.76	0.30	-0.03	-0.28
	(1.94)	(1.55)	(0.5)	(-0.08)	(-0.66)

Table 7: Momentum returns and market turnover

At the end of each month *t*, all stocks are allocated into quintiles based on their lagged 6-month (*t*-6 to *t*-1) returns, skipping month *t*. These portfolios are held for six months (*t*+1 to *t*+6). Following Jegadeesh and Titman (1993), portfolios are rebalanced monthly. Low and High Market Turnover is defined by dividing the full sample into two groups based on market turnover from *t*-11 to *t* month. Monthly average returns of P1 (Loser), P5 (Winner), P5-P1 (momentum returns), MP (market portfolio), WMMP (winner minus market portfolio) and CAPM and Fama-French alphas over the sample period are reported below. A-B represents the difference in momentum returns between Low and High market turnover. All the returns are reported in percent and their *t*-statistics provided in parentheses. The sample period is from January 1995 to December 2015.

E-W Momentum returns following 12-month market turnover			
	Low(A)	High(B)	A-B
N	114	126	
P1 (Losers)	0.81	3.06	
	(0.87)	(3.18)	
P5 (Winners)	1.64	2.60	
	(1.91)	(2.70)	
P5-P1	0.84	-0.46	1.30
	(2.27)	(-1.57)	(2.78)
MP	1.22	3.18	
	(1.39)	(3.33)	
WMMP	0.43	-0.58	
	(2.03)	(-3.24)	
CAPM-ALPHA	0.85	-0.42	1.27
	(2.33)	(-1.42)	(2.73)
FF-ALPHA	0.95	-0.14	1.09
	(2.75)	(-0.48)	(2.42)

Table 8: Momentum returns, lagged and contemporaneous market states (Exclusion of 2007 and 2015)

At the end of each month *t*, all stocks are allocated into quintiles based on their lagged 6-month (*t*-6 to *t*-1) returns, skipping month *t*. These portfolios are held for six months (*t*+1 to *t*+6). Following Jegadeesh and Titman (1993), portfolios are rebalanced monthly. Non-negative (negative) Value-Weighted Market Returns over months *t*-11 to *t* and value-weighted contemporaneous market returns over the month of *t*+1 are used to define UP/UP, UP/DN, DN/UP and DN/DN market states. If lagged market returns and contemporaneous market returns are non-negative (negative), the market state is designated as UP/UP (DN/DN). If lagged market returns are non-negative (negative), and contemporaneous market returns are negative (non-negative), then the market state is defined as UP/DN (DN/UP). Monthly average returns of P1 (Loser), P5 (Winner), P5-P1 (momentum returns), MP (market portfolio), WMMP (winner minus market portfolio) and CAPM and Fama-French alphas over the sample period are reported below. A-B represents the difference in momentum returns between UP/UP and UP/DN markets, while C-D represents the difference in momentum returns between DN/UP and DN/DN markets. All the returns are reported in percent and their *t*-statistics provided in parentheses. The sample period is from January 1995 to December 2014.

Momentum returns following 12-month and contemporaneous market returns (excluding 2007 and 2015)						
	UP/UP(A)	UP/DN(B)	A-B	DN/UP(C)	DN/DN(D)	C-D
N	60	44		54	58	
Loser (Formation)	-1.41	-1.94		-5.15	-4.63	
	(-5.08)	(-5.41)		(-18.44)	(-25.27)	
Winner (Formation)	15.48	14.68		5.38	4.75	
	(17.95)	(13.78)		(10.00)	(12.94)	
P1 (Holding)	7.07	-5.14		8.31	-6.67	
	(8.95)	(-5.90)		(7.4)	(-7.95)	
P5 (Holding)	6.77	-4.90		7.79	-5.35	
	(7.84)	(-5.72)		(7.92)	(-5.71)	
P5-P1	-0.29	0.25	-0.54	-0.52	1.32	-1.83
	(-0.53)	(0.59)	(-0.73)	(-1.02)	(2.83)	(-2.83)
MP	7.17	-4.80		8.13	-5.97	
	(9.24)	(-5.78)		(7.86)	(-7.18)	
WMMP	-0.39	-0.10		-0.33	0.62	
	(-1.20)	(-0.39)		(-1.22)	(2.30)	
CAPM-ALPHA	-0.13	0.11	-0.24	-0.35	1.19	-1.54
	(-0.24)	(0.26)	(-0.33)	(-0.70)	(2.52)	(-2.41)
FF-ALPHA	0.10	0.47	-0.37	-0.30	1.21	-1.51
	(0.18)	(1.25)	(-0.50)	(-0.67)	(2.61)	(-2.27)