Retail Investors and Momentum

Jun Du

Dashan Huang

Yu-Jane Liu

Yushui Shi

Avanidhar Subrahmanyam

Huacheng Zhang

December 2022

Du and Liu are from the Guanghua School of Management, Peking University. Huang is from Singapore Management University. Shi is from the Monash Business School, Monash University. Subrahmanyam is from the Anderson School, UCLA. Zhang is from the University of Nottingham. Please address all correspondence to Yushui Shi, email: yushui.shi@monash.edu.
We thank David Hirshleifer, Christopher Polk, Richard Sias, Susanne Siedhoff, Baolian Wang, Wei Xiong, participants at the 2022 Miami Behavioral Finance conference and the 2022 Australian Finance and Banking Conference, and in seminars at University of International Business and Economics (Beijing) and the University of California at Irvine, for valuable comments. We are grateful to Terrance Odean for granting us access to his discount brokerage data.

Retail Investors and Momentum

Abstract

We explore the link between momentum and investing clientele via an identification strategy for retail participation. Specifically, due to a strictly-implemented roundlot restriction, small retail investors are less prone to participating in Chinese stocks with high nominal prices. In turn, there is strong momentum in stocks with high nominal prices, but no momentum on aggregate. Short-term reversals are stronger in low-priced stocks. Institutional holdings enhance momentum in high-priced stocks. Small investor participation increases and momentum weakens following splits in high-priced stocks. The results support the notion that retail trades contribute to short-term reversals, while institutions contribute to momentum.

JEL codes: G14, G41

Keywords: Momentum, Retail investors, Nominal stock prices

Since the discovery of momentum in U.S. equities by Jegadeesh and Titman (1993), the profitability of this simple strategy that buys past winners and shorts past losers has continued to puzzle researchers. Chui, Titman, and Wei (2010), and, more recently, Liu, Stambaugh, and Yuan (2019) find that momentum is largely absent in the Chinese market. This difference in momentum profits between U.S. and China, two of the world's top equity markets by capitalization, raises intriguing questions. For example, is momentum pervasively absent in China or is it present in a subset of stocks? And, what can we learn about momentum in general from the behavior of momentum profits in China?[1]

To address the above questions, our starting point is the observation that the Chinese market has a much stronger presence of retail investors.[2] In general, such investors are considered to be unsophisticated traders, who might naïvely conduct short-horizon trades (Jones et al. 2022), and whose demands can cause inventory-based return reversals (Nagel 2012; Peress and Schmidt 2020; Chui, Subrahmanyam, and Titman 2022). On the other hand, other work suggests that better informed (e.g., institutional) investors' underreaction to fundamentals due to cognitive or agency limitations leads to return momentum (Hong and Stein 1999; Cao, Han, and Wang 2017). These observations imply that a greater presence of short-horizon retail investors promotes short-term reversals, while

[1] We recognize that there are other stylized facts surrounding momentum. For example, it is more prevalent in bull markets, which might explain why it has not been detectable in Japan (Cooper, Gutierrez, and Hameed 2004). Momentum profits also have diminished over time in the U.S. (e.g., Chordia, Subrahmanyam, and Tong 2014). Büsing, Mohrschladt, and Siedhoff (2022) show stronger momentum when the past return is measured going backward from the highest price in the formation period. For parsimony, however, in this paper we focus on traditional ways of measuring momentum, and what we can learn from the Chinese context.

[2] Blair (2018) states that domestic retail investors accounted for about 85% of trading volume in Chinese shares during 2015. The corresponding number for the U.S. is just 10% (https://tinyurl.com/3ve5kzx4).

the prevalence of sophisticated investors like institutions promotes longer-term momentum.[3]

While the above arguments identify a path by which clienteles may influence momentum, the reliability of evidence on this issue requires plausible identification schemes. In this paper, we test for such a clientele-momentum link via a two-prong identification approach that uniquely applies in Chinese equities. In our first method, we identify firms in which retail investors are less (more) active for reasons other than firms' fundamentals, and examine whether there is in fact more (less) momentum in these shares. Our second approach exploits a corporate event that increases retail investor participation, and examines whether the profitability of momentum strategies decreases as a result.

Specifically, we first exploit a Chinese market rule that makes retail investors less prone to investing in stocks with high nominal prices. The rule sets the minimum trading unit at a roundlot of 100 shares.[4] Such a requirement, which is enforced *without exception*, induces financial constraints on less-wealthy ("small") investors. Because these constraints are only related to investors' capital and nominal prices, but unrelated to firms' fundamentals,[5] nominal prices affect participation by small investors in a manner independent of underlying cash flows.

[3] Chui, Subrahmanyam, and Titman (2022) show that Chinese B shares do exhibit momentum, and attribute this to a lower prevalence of retail investors in these shares. However, the sample of firms that issue both A and B shares is small (less than ninety firms), thus limiting the generality of conclusions that can be drawn from their scenario.

[4] The rule can be found on the Shanghai Stock Exchange website (http://www.sse.com.cn/lawandrules/sselawsrules/stock/trading/main/).

[5] Nominal price is not among the set of stock characteristics that predict stock returns, over and above standard anomalies related to size, book-to-market ratio, asset growth, past performance, and profitability. We have not found a nominal-price-related anomaly in the Chinese market.

We use account-level data to show how investors' financial constraints, that are a function of their portfolio wealth, affect their propensities to invest in high-priced stocks. We designate retail investors whose average portfolio size is below 200k (above 500k) yuan as "small" ("large").[6] We find that small investors have shorter average holding periods and higher turnover than larger investors, supporting that the former are short-horizon traders. We then directly measure investor groups' participation propensity across deciles based on nominal prices.[7] We find that this propensity is negatively related to stock prices. The downward slope is much steeper for small investors than for large investors. For example, compared to the stocks in the fifth decile group, the participation propensity in the tenth decile (highest-priced group) drops by 53.5% for small investors, whereas the corresponding reduction is just 20.7% for large investors.

We use two other tests to show that high prices deter small investors via the financial constraint channel. First, we show that as the prices of high-priced stocks rise, their direct holdings amongst small investors decrease, whereas their indirect holdings via mutual funds continue to increase. Second, we show that when stocks held by small investors experience long-lived trading halts, thus effectively locking up wealth, such investors reduce their propensity to buy high-priced stocks (but not low-priced stocks).

We then test our main hypothesis that momentum is stronger in stocks with less ownership by small retail traders. Based on the previous results, we consider nominal price as a quasi-exogenous proxy for retail investor participation. We thus examine the returns of momentum strategies across stock groups

[6] The current exchange rate is about 6.7 yuan per U.S. dollar. According to Jones et al. (2022), investors with portfolio sizes below 100k yuan account for approximately half of all investors in Shanghai Stock Exchange.

[7] Because retail investors cannot short-sell stocks (they can sell only after initially buying), their propensity to hold a stock maps closely to the probability of their buying or selling that stock.

conditional on price. For this purpose, we are able to use a longer time series of returns data from January 2000 to December 2020, relative to the 2016-2020 time series for the trading account data. Consistent with Griffin, Ji, and Martin (2003), Chui, Titman, and Wei (2010), and Docherty and Hurst (2018), the 12-month momentum strategy based on going long-short in the extreme winner-loser quintiles generates insignificant monthly returns on aggregate (estimate = 0.212% and *t*-value = 0.82). In a novel result, however, among the highest-priced stocks (the tenth decile), the momentum strategy generates significantly positive monthly returns (estimate = 1.662% and *t*-value = 4.00). This monthly return estimate translates to an annual return of 19.94%.[8] If one yuan is invested in the momentum strategy among the highest-priced stocks, it multiplies to approximately 30 yuan over the sample period, which is five times greater than the corresponding number for the momentum strategy that applies to all stocks. Our qualitative results are robust to controlling for risk factors, using double-sorted portfolios, and using Fama and MacBeth (1973)-type regressions.

The dampening effect of small retail investors on a baseline level of momentum suggests that the marginal impact of such investors should diminish as their presence increases, but the momentum returns should not turn negative. We indeed find evidence supporting this notion. Specifically, the returns of momentum strategies halve from the highest-priced decile (1.662% per month) to the second-highest one (0.732% per month and still statistically significant). The average return further declines to 0.072% (*t*-value = 0.16) in the lowest price decile group. Thus, the point estimates of momentum profits are positive, but their economic and statistical significance diminish as we move to progressively lower-price deciles.

---

[8] It may be of interest to consider the nature of the relation between retail participation and momentum in the U.S. We address this issue in Section 4.4.

We also demonstrate two other findings. First, short-term reversals are more pronounced in low-priced stocks,[9] a pattern which is the opposite of that for 6-12 month momentum.[10] Second, for the high-priced stocks, where we *do* find momentum, we find that such momentum is more pronounced for stocks with higher levels of institutional holdings.[11] The overall picture thus conforms to the notion that retail noise trading exacerbates short-term reversals and attenuates momentum, while institutions contribute to momentum.[12]

We next use a corporate event, namely, stock splits, to corroborate that financial constraints cause low participation of small investors among high-priced stocks, thus resulting in lower momentum in these stocks. Since splits mechanically lower nominal prices, they make the stocks more affordable to small investors. As a result, we expect a net increase in the fraction of small investors and, in turn, a decrease in the momentum effect.[13] In a standard event-study approach, we indeed find that for the high-priced stock groups, stock splits lead to a 25.7% increase in participation among small investors and only a 10.7% increase in large investor participation. These results are consistent with our financial constraint hypothesis because small investors face tighter financial constraints than large investors.

[9] We show in the paper that this result prevails even after controlling for illiquidity.

[10] Jegadeesh et al. (2022) estimate the order imbalances of retail investors (using the method of Boehmer et al. 2021), and link these imbalances to monthly reversals. But they do not link retail investors to momentum.

[11] This finding is consistent with the underreaction hypotheses of Hong and Stein (1999) and Cao, Han, and Wang (2017) as well as the institutional feedback trading hypothesis of Lou (2012) and Vayanos and Woolley (2013). Grinblatt, Titman, and Wermers (1995) show that mutual funds are prone to following momentum strategies.

[12] In Appendix B we present a simple model that formalizes this intuition.

[13] Various papers use stock splits to investigate investors' anomalous behavior in response to changes in nominal prices (Birru 2015; Birru and Wang 2016; Hu, Liu, and Xu 2021; Shue and Townsend 2021).

To further distinguish the financial constraint hypothesis from alternative hypotheses such as investor attention (Ikenberry and Ramnath 2002; Almazan, Banerji, and Motta 2008; Titman, Wei, and Zhao 2022) or gambling (Kumar 2009; Hu, Liu, and Xu 2021), we use the split ratio as the mediating variable. The intuition is that, under the financial constraint hypothesis, higher split ratios mean lower after-split prices, more loosened small investors' financial constraints and, in turn, more participation from small investors. On the other hand, there is no clear reason to believe that higher split ratios are associated with stronger signaling motives, or are more attention-grabbing. We show that indeed, the increase in small investor participation is stronger when split ratios are higher. We conclude that the increase in the net fraction of small retail investors after stock splits is most likely due to loosening of financial constraints, especially for the high-priced stock groups.

We next examine how stock split events affect stock-level momentum.[14] We show that for the high-priced stock group, stock splits dampen stock-level momentum by 6.3% post-split, and the dampening effect is strengthened with higher split ratios.[15] Further, the estimate of the after-split effect is close to zero and statistically insignificant for the rest of the stocks. Overall, these results confirm our hypothesis that small retail investors attenuate momentum profits.

The question naturally arises as to what is novel about our Chinese setting that helps us understand momentum. The answer lies in the special features of

[14] However, we need to mention a caveat: Firms may use stock split events to manipulate stock prices in the short-term by attracting retail investors for liquidity reasons (Titman, Wei, and Zhao 2022). To the extent that investors have limited attention, a heightened attention on splitting stocks may increase the probability of retail investors trading those stocks. The basic notion that retail investors attenuate momentum would still be applicable here.

[15] In terms of reverse causality, while splits do target retail investor participation for liquidity reasons, it is less plausible to argue that they target the additional noise trading that masks momentum.

our data.[16] In general, establishing a causal relationship between retail investors and asset prices is difficult, because it is challenging to create a treatment and control markets with different clienteles. The Chinese context uniquely exploits a strictly-implemented roundlot rule to strengthen identification of the pathway from investing clientele to return momentum, compared to correlational studies between market participation and return predictability in an international setting. Our evidence on direct stockholdings versus indirect holdings via mutual funds, the effect of long-lived trading halts on retail investment, and the effect of splits on retail investment, is uniquely facilitated via access to detailed Chinese data on retail holdings and trading activity. Through these identification schemes that establish nominal stock prices as an inverse proxy for retail investment, we are able to shed light on the link between momentum and retail investors. [17]

We note that new and inexperienced retail investors have increased their presence in the U.S stock market since the COVID-19 pandemic and are linked to stock market frenzies (e.g., Barber et al. 2022; Hu et al. 2021). If this new generation of retail investors forms a permanent presence, what implications does this have for return predictability going forward? Our study on the Chinese market may provide an early glimpse into this question. The results suggest that

[16] Other literature has also exploited the richness of Chinese market data to document various asset pricing phenomena (e.g., pricing irregularities, market frenzies, and bubbles) that can be linked to retail investors' irrational behavior (e.g., Xiong and Yu 2011; Chen et al. 2019; Gao et al. 2020; Li, Subrahmanyam, and Yang 2021; and Pearson, Yang, and Zhang 2021).

[17] Our analysis focuses on the cross-section of stocks within China, but also suggests that the difference in momentum between U.S. and China is because the additional retail noise trading in China masks momentum. Although Chui, Titman, and Wei (2010) argue that the U.S.-China difference in momentum arises because collectivist Chinese investors are less overconfident which should lead to lower momentum (Daniel, Hirshleifer, and Subrahmanyam 1998), recent evidence (Li, Chen, and Yu 2006; Yates et al. 1998) shows that Chinese subjects demonstrate greater overconfidence than Western ones. Thus, there is room for multiple explanations for why momentum varies across the U.S. and China.

such markets might effectively shorten average trader horizons and thus might interfere with momentum over the typical 6-12 month horizons.

Many theoretical papers on momentum focus on investors' biased beliefs (Daniel, Hirshleifer, and Subrahmanyam 1998; Barberis, Shleifer, and Vishny 1998; Hong and Stein 1999; Da, Gurun, and Warachka 2014; Andrei and Cujean 2017). We believe that biases play an important role in generating momentum. However, it is tempting to conclude that if a return anomaly is caused by biased belief updating, then the absence of such an anomaly suggests rationality. Our results propose instead that overall momentum in China is obscured by retail noise trading. Thus, our work exemplifies that even though a return anomaly might be absent in a market, it does not imply the predominance of rational investors in that market.

The paper is also broadly related to the literature on retail investors' aggregate trades and their impact on stock prices. The literature has found that retail trades have a systematic component (Kumar and Lee 2006; Barber, Odean, Zhu 2008) and can predict future returns (Kaniel, Saar, and Titman 2008; Barber et al. 2009). Further literature has pointed to heterogeneity among retail investors in their investment strategies, such as momentum versus contrarian trading (Grinblatt and Keloharju 2000; Goetzmann and Massa 2002; Jones et al. 2022). Our results show the importance of distinguishing between small and large retail investors, and their relative effects on momentum.

1. Data and price-based financial constraints

In this section, we introduce our account level data and describe portfolio characteristics across investor groups. Then, we define a price-based constraint which originates from a roundlot rule that applies to Chinese investors.

1.1 Account level data

The primary source used in this study includes account level data for 103,113 retail investors who trade via a large Chinese discount brokerage.[18] We have investors' monthly position statements from January 2016 to June 2020 and their trades from January 2018 to June 2020. The data capture investments in common stock and mutual funds. The trade data include an investor identifier, the date of the transaction, the security identifier, the price at which the transaction was carried out, the number of shares associated with the transaction, the buy/sell indicator, and the total value of the transaction. The data for monthly position statements include the investor identifier, the date of the statement, the security identifier, the price as of market close on the statement date, the number of shares held, and the total value of the position in the security. The data also contain demographic information about households such as their gender, age, education, and venue of account opening.[19]

In our study, portfolio wealth plays an important role in defining the potential financial constraint faced by investors. Therefore, we define investors whose time-series average portfolio size is below 200k yuan (above 500k yuan) to be small (large) investors.[20] Large investors serve as a control group for small

---

[18] By Chinese government policy, retail investors can hold up to three accounts from different brokerage companies per citizen ID. Retail investors may switch between different companies, but it is uncommon for them to split their wealth across different accounts because brokerage companies incentivize them to consolidate by offering commission fee discounts and premium customer services.

[19] While our account-level data do not contain information about household income or wealth, according to a survey conducted by Southwestern University of Finance and Economics in 2021, Chinese households have a total wealth of 1.21 million Yuan, of which financial assets are worth 112 thousand Yuan. Bank savings account for more than half of the financial assets (57.8%) and stock investments account for 15.5%.

[20] The specific choices on cutoffs used here are in part based on the consideration of having enough observations under each investor group. In our sample, small (large) investors account for 43.5% (35.7%) of the total accounts. We also try alternative cutoffs, for example, below 100k yuan for small investors and above 1 million yuan for large investors and find robust results.

investors in terms of price constraints. To put these numbers in perspective, according to Jones et al. (2022), investors with portfolio sizes less than 100k yuan (more than 500k yuan) account for 58.7% (12.7%) of retail investors in the Shanghai Stock Exchange.

Although the number of investors included in our data is smaller than that in the comprehensive dataset of Jones et al. (2022), our dataset nonetheless consists of more than 100,000 investing accounts. The size of the sample provides reassurance on the reliability of our analysis documenting differences in investor groups' participation propensity across high- versus low-priced stocks. In addition, unlike Jones et al. (2002), our data provides us access to each account's complete trading history, which enables us to test how their participation propensities change after exogenous shocks to financial constraints (such as stock splits or long-lived trading halts).

We present the basic stock portfolio characteristics for small and large investors in Table 1 Panel A. Specifically, we present different percentile values for the variables mentioned in the leftmost column of each row. Among small investors, the average (median) value per stock is approximately 22k (14k) yuan during our sample period. Moreover, small investors tend not to diversify their account holdings; they own an average of 3.4 stocks in their brokerage account. Small investors also trade less frequently than large investors, at 13.6 times per month on average. The mean and median trade sizes for small investors are 17.5k yuan and 10.4k yuan, respectively.

[Insert Table 1]

On the other hand, the median investor in the large investor group has an average value per stock of 226.8k yuan during our sample period. The mean and median trade sizes for large investors are 128.3k yuan and 67.4k yuan, respectively. On average, large investors hold more diversified portfolios (8.2 stocks in their portfolios) and trade more frequently (26 times per month) than small investors.

We also find that small investors have a shorter holding period than large investors (58 days vs. 103 days) and turn over their positions more frequently (mean annualized monthly turnover of 214 vs. 147). This is indicative evidence that small investors have shorter investment horizons. They also hold stocks with lower prices than average (12.0 vs. 18.4).

1.2 Price-based constraint

Next, we introduce the key concept in this paper: price-based constraints. In normal circumstances, nominal prices should not factor into investor demand. Imagine an investor who decides to invest 5,000 yuan in a specific stock. If the stock price is set at 5 yuan per share, the investor will buy 5,000/5 = 1,000 shares; if the stock price is alternatively set at 10 yuan, the investor will buy 5,000/10= 500 shares instead. However, in the Chinese market, a *strict* roundlot rule applies such that investors must buy or sell stocks in units of 100 shares. The direct consequence of this rule is to impose an upper limit on the stock price an investment can accommodate. In our example, if the stock price is greater than 50, then an investment of 5,000 yuan cannot buy the minimal 100 shares of the stock; that is, the investment hits its price constraint.

The roundlot rule was introduced into the Chinese securities market in the 1990s. It was instituted to ease the settlement burden from small trades because Chinese citizens could easily trade stocks at local brokerage branches, bringing in millions of orders in small amounts. Figure 1 shows the distribution of stock prices from 2000 to 2020. The price dispersion has increased over time. The average price of the high-priced stock groups (those in the 10th or 9th decile) has grown disproportionately faster than those of other stock groups. In other words, the constraint imposed by the round lot rule has become much more stringent in recent decades, which, we believe is an unintended consequence of this rule.

[Insert Figure 1]

For our purposes, we measure the price constraint for each investor as the stock price above which the average investment amount per stock position cannot afford to hold at least 400 shares of the stock. There are two assumptions underlying this definition. First, we assume that retail investors tend to trade stocks using a mental account, replacing each stock in their portfolio with another (Kumar and Lim 2008). This means that funding for new stock positions come from sales of existing positions. Second, we use 400 shares as an estimate of the "practical" limit, because a stock with a sufficiently high price such that a small investor could just about buy 100 shares would mean the ability to either take a 100 share position or no position in the stock. In practice, investors likely would want the ability to adjust their exposure to the stock. For instance, if the high-priced stock outperforms the investors' other positions, the investor may want to rebalance their portfolio by selling just a portion of their position in the high priced stock. Empirically this seems to be the case, as shown in Table 1, although the median small investor only holds 2.6 stocks, more than 90% of small investors hold at least 400 shares of each position on average. Overall, the price-based financial constraint we propose is not a “hard” line that investors cannot cross but a “soft” one.

Table 1, Panel A reports the distribution of the price-based constraint—that is, the imputed maximum price below which an investor can frictionlessly hold a stock position in their portfolio—for large and small investor groups. The median price-based constraint for small investors is 36.1, which is close to the

90th percentile of the average stock price, 40.2. This means that about half of the small investors are prone to exclusion from trading the highest-priced stocks. In contrast, the median price-based constraint among the large investors is 567.0, which is much higher than the 99th percentile of the average stock price, 115.8.[21] Overall, therefore, the evidence suggests that smaller investors are much less likely to trade high-priced stocks than large investors, because of financial constraints. In untabulated results, we have verified that this qualitative conclusion is robust to using alternative scale factors of 300 or 500 shares to identify the price constraint. In each of these alternative cases, the price threshold is at least fifteen times higher for large relative to small investors.

1.3 Other data

We obtain stock market data from the China Stock Market & Accounting Research (CSMAR) database, which contains information regarding stock returns, nominal share prices, daily turnover, market value of float, market capitalization, and institutional ownership. We restrict the stock sample to A-shares that are publicly traded on the Shanghai Stock Exchange or the Shenzhen Stock Exchange. Our sample period for the asset pricing part of the paper is from 2000 to 2020. This follows prior studies on the Chinese stock market (e.g., Liu, Stambaugh, and Yuan 2019; Titman, Wei, and Zhao 2022); this market is relatively undeveloped prior to 2000, and the reliability of pre-2000 data is questionable. We implement the following filters: 1) we delete Special Treatment (code ST or ST-plus) stocks

[21] We also ascertain that for small investors the purchase of highest-priced stock is unlikely to be funded by regular cash injections. To show this, for each investor, we first calculate the monthly net cash inflow as the change in cash balances, plus the total sell volume, and minus the total buy volume. Then, we calculate the time-series average of the monthly cash injection by conditioning on the positive monthly net cash inflows. By dividing the average cash injection by 400 shares, we find that for the median small investor, the price-based constraint is 16.0, which is much lower than the 90th percentile of the average stock price. The detailed table is available upon request.

or Particular Transfer (code PT) stocks; 2) we delete the smallest 10% of stocks based on market capitalization as of the current month; and 3) we remove stocks with nominal prices less than 3 yuan as of the current month. The last two filters ensure that our results do not emanate from microcap stocks or those with extremely low nominal prices.

2. Small investor participation propensity

We start by investigating the participation propensity of small investors in high-priced stocks relative to low-priced ones. For each month, we divide stocks into deciles based on nominal price at the previous month-end. We then measure the participation propensities within each decile stock group, for each investor group, as the proportions of investors who hold stocks in that decile group. Table 1, Panel B summarizes the propensities for small and large investors. We find that there is an inverse relationship between stock price and participation propensity for both small and large investors. Note that the average propensity is much higher for large investors than small investors because large investors, on average, hold more stocks in their portfolios. Therefore, we normalize the propensities relative to the propensity for the fifth price-based decile, for each investor group, and depict the pattern in Figure 2.

[Insert Figure 2]

The figure shows that while participation propensity is negatively related to stock prices for both investor groups, the downward slope is much steeper for small investors. Specifically, compared to the fifth decile, the participation propensity in the tenth decile is reduced by 53.5% for the small investor group, and only by 20.7% for the large investor group. We conclude that because small investors face much tighter price-based constraints than large investors, there is a smaller fraction of small investors investing in high-priced stocks.

Our identification strategy hinges on the assumption that reduced investor participation of small investors in high-priced stocks is due to financial constraints and not due to other aspects. A confounding effect is that investors may have specific preferences for low stock prices that might directly affect their investment decisions. Indeed, a line of literature has found that retail investors, especially small investors, tend to prefer low-priced stocks due to gambling preferences (Kumar 2009) or nominal price illusion (Birru and Wang 2016). To investigate this preference, we calculate the average portfolio weights for each price-based decile stock group. Table 1, Panel B shows that small investors tend, on average, to invest more in low-priced stocks than in high-priced stocks in their portfolios. For example, their average holding percentage for the lowest-priced decile group is 15.5%, whereas that for the highest-priced decile group is 7.1%. In contrast to small investors, the relationship between the average holding percentage and stock price flips sign for large investors. The magnitude is relatively small, however, and the relationship is nonmonotonic.

One possible way to shed light on the confounding effect of small investors preferring low-priced stocks is to look for patterns outside of the very low-priced stocks (defined as those with below-median prices). Table 1, Panel B shows that from the first decile group to the fifth decile group, the average holdings percentages for small investors decrease from 15.5% to 9.3%, whereas from the fifth decile group to the tenth decile group, the percentages still decrease, albeit by a smaller amount, from 9.3% to 7.9%. The 53.5% proportional decrease (from 21.3% to 9.9%) in investment participation from medium-priced to high-priced stocks is unlikely caused by investors' preference for low-priced stocks.

To further investigate the robustness of our results, we compute the participation propensities for different definitions of small investors and large investors (below 100k yuan and above 1M yuan, respectively). Table A.1 in Appendix A shows similar results. We also define small and large investors based on their average portfolio size over the past six months (on a rolling basis), rather than across the whole sample; the results, not tabulated for brevity, are similar.[22]

3. Stock prices and retail participation: Further evidence

In this section, we provide further evidence that stock prices influence participation via the financial constraint channel due to the roundlot restriction.

3.1 Individual stocks versus mutual funds

One alternative possibility is that small investors may erroneously believe that high-priced stocks have less growth potential than low-priced stocks, and thereby invest less in the former (Birru and Wang 2016). To assuage this concern, we look at a subset of retail investors who invest simultaneously in individual stocks and mutual funds. The idea is that financial constraints would result in increased indirect holdings of high-priced stocks via mutual funds, because financial constraints are absent in funds' investment. On the other hand, pessimistic beliefs about high-priced stocks would impact direct and indirect holdings symmetrically.

We first consider a single visible stock, Moutai—a spirit company, which had the highest nominal share price in China during our sample period; its price averaged one thousand yuan. The high popularity of Moutai helps to enhance the likelihood that investors who buy funds that hold Moutai are explicitly aware of investing indirectly in Moutai.

[22] Using this approach helps alleviate the concern that poor stock performance simultaneously lowers stock prices and investor portfolio size. Under this rolling definition, we find that the large and small investor grouping is very persistent: there is 98.6% (98.4%) probability that small (large) investors identified in the last month remain in the same group in the current month.

We calculate the average portfolio weight on Moutai among small investors for their individual stock holdings and fund holdings, respectively. Figure 3, Panel A shows the time series of the portfolio weights. We find that the average direct holdings of Moutai among small investors level off at low levels, while the price of Moutai keeps rising during our sample period. On the other hand, the average implied holding percentages of Moutai via funds whose top-ten holdings include Moutai,[23] instead of leveling off, parallel the time trend of Moutai prices. These results suggest that small investors who cannot afford to buy Moutai invest in mutual funds to indirectly hold Moutai. We also run a placebo test on large investors who are less susceptible to financial constraints. Interestingly, in this case, the direct holding percentage of Moutai rises in tandem with the indirect counterpart. Overall, these results are consistent with our financial constraint hypothesis.

[Insert Figure 3]

We next generalize the above finding to groups of stocks with prices higher than 100 or, in turn, 50 yuan. The power of our test increases with the number of stocks being included, but it is less certain that investors are clearly aware of the stocks held by the funds in which they invest. However, we count only the stocks that are among funds' top-ten largest holdings, which partially alleviates the awareness concern. In general, we find similar results. For small investors, direct holdings are much lower than indirect holdings of the high-priced stocks. On the other hand, such a wedge between the direct and indirect holdings is nearly absent for large investors. Thus, the tests suggest that the reduced participation

[23] In Figure 3, we only count those funds for which Moutai is among the top ten holdings in the fund's most recent quarterly report. The weight of Moutai relative to the fund's total holdings is calculated based on the fund's most recent quarterly report and reset each quarter.

propensity of small investors on high-priced stocks is unlikely due to investors' beliefs, but rather, due to financial constraints.

3.2 Diff-in-diff test with trading halt events

The previous test which uses direct and indirect holdings notwithstanding, an omitted variable might still drive the negative relationship between investor participation and stock price. To better account for this issue, we exploit trading halt events that induce negative exogenous shocks on investors' portfolio wealth and, in turn, on their financial constraints.

Trading halts imply a complete shutdown of trading in the affected stock and can last for as long as a month or more.[24] In these cases, investor holdings are frozen, which means that investors cannot sell the corresponding shares to facilitate the purchase of other stocks should the need arises. Therefore, we propose that long-lasting trading halts exert exogenous shocks on individual investors' disposable capital when they happen to hold the affected stocks in their portfolio. We acknowledge that the trading halt events do not occur randomly, and investors may to some degree anticipate the occurrence of trading halts. However, it is hard for small retail investors, who are extremely unlikely to have inside information (Peress and Schmidt 2020), to know the exact time and duration of trading halts. We propose that such unanticipated, long-lived halts lock up part of small investors' wealth and make them seek low-priced stocks with their remaining wealth.

[24] On the Shanghai Stock Exchange (SSE), trading halts are divided into three types: halts due to abnormal price fluctuations, which last for at most a few hours; halts due to shareholders' meeting which usually last for one day; and halts due to significant corporate events, such as M&A discussions and processes, which can last for several months.

To test the above conjecture, we deploy a diff-in-diff test using a series of trading halt events that last for at least one month. We compare the buy propensity of affected investors for high-priced stocks after these stocks experience trading halt events with that of comparable investors who do not experience such events during the same period. Because we include an individual-specific fixed effect, we control for any time-invariant investor-specific beliefs or preferences on high-priced stocks.

We implement the test via the following steps. First, we identify a sample of 58 trading halt events that last for at least one month. Second, we identify "treated" investors as those small investors who hold a stock that experienced a trading halt event and consider the investors' trades during the three months before and after the month of the trading halt. We consider those investor-halt-event observations for which the affected stock accounts for more than 10% of the investor's portfolio at the end of the calendar month just prior to the halt. Third, we construct a control group using investors who do not experience any trading halt events during our sample period. We match each investor-halt-event observation from the treatment group with three investors from the control group during the same period. The matching variables are portfolio size and trading propensity for high-priced stocks (the proportion of trading volume in stocks with prices above the 80th percentile), measured three months prior to the event-month. In total, we have 296 investor-halt-event observations for the treatment group and 788 investor-stock-event observations for the control groups.

We estimate the following regression:

$$Buy\_high_{i,t} = \alpha + \beta_1 Treat_i \times Post_{i,t} + \tau_t + \nu_i + \varepsilon_{i,t}, \quad (1)$$

where $Buy\_high_{i,t}$ denotes the share of buy volume in high-priced stocks (above the 80th percentile) relative to the total buy volume for investor i at day t; $Treat_i$ is a dummy variable that is unity for investors in the treatment group, and zero otherwise; $Post_{i,t}$ is a dummy variable that is unity if day t is within the window of the trading halt event associated with investor i, and zero otherwise. Investor-day observations are limited to investor-days where the investor makes at least one buy trade. The regression also includes investor and time fixed effects to control for observed and unobserved heterogeneity across investors and across dates. The coefficient of interest, β_1, captures the impact of the trading halt events on investor behavior of buying high-priced stocks.[25]

Table 2, Panel A shows the results of the diff-in-diff regressions for small investors. Column (1) shows that the coefficient on β_1 is -0.052 (t-value = -2.74), which suggests that trading halt events induce small investors to reduce their propensity to buy stocks with price levels greater than the 80th percentile than otherwise similar, unaffected investors. Regarding the economic magnitude, this coefficient estimate corresponds to a 15.7% reduction relative to investors' average buy propensity of 33.2% prior to the events. Column (2) shows robust results including both investor and day fixed effects (estimate = -0.041 and t-value = -2.78).

[Insert Table 2]

We also run placebo tests on large investors, for whom we expect that the trading halt events have a minor effect. In line with our expectation, the estimate of β_1 amounts to only -0.021 as compared to -0.052 for small investors and is

[25] In untabulated tests, we find that we fail to reject the null of parallel trends in *Buy_High* across treated and control groups.

statistically insignificant (column (3) of Table 2). The results are robust if we control for investor and day fixed effects.[26]

To sum up, we find robust results which indicate that small investors' participation propensity significantly decreases with an increase in nominal stock prices. The evidence using direct-versus-indirect holdings via funds, and trading halts, supports the notion that high stock prices impose financial constraints on small investors' relatively limited wealth, thus limiting such investors' participation in stocks with high nominal prices. These findings suggest that stock price levels can serve as a quasi-exogenous proxy for the presence of small investors within the market for a stock.

4. Stock prices and momentum

In the previous sections, we link retail investor participation to nominal price, using account level data from 2016 to 2020. We now focus on asset pricing tests using a longer time-series of Chinese stock market returns (from 2000 to 2020). Our working hypothesis is that the short-horizon trades of small retail investors (Jones et al. 2022) tend to cause short-term reversals (Peress and Schmidt 2020; Nagel 2012), and attenuate momentum caused by underreaction to news by relatively sophisticated investors such as institutions due to cognitive limitations or agency issues (Hong and Stein 1999; Cao, Han, and Wang 2017). Appendix B presents a simple setting that formalizes these arguments.[27]

---

[26] We also run a version of equation (1) where the left-hand variable, in turn, is the buy propensity in the 40th to 60th percentile, and below the 20th percentile of stock prices. The coefficient of $Treat_i \times Post_{i,t}$ is not significant in these cases, which confirms the notion that long-lived trading halts specifically deter small investors from buying high-priced stocks.

[27] Akbas et al. (2022) show that short-horizon institutions can mistakenly attribute a sequence of positive daytime returns to noise trading and overcorrect prices, which may reduce future returns. This finding, however, does not directly relate to monthly reversals and momentum over longer periods.

In Section 4.1 below, we examine whether small investors' participation in the Chinese market, as proxied by nominal prices, affects momentum returns using portfolio sorts. Section 4.2 considers short-term reversals, Section 4.3 corroborates our results for the Chinese market using regressions, Section 4.4 discusses our implications of our results for the U.S.

4.1 Portfolio sorts on prices and momentum

First, we independently sort stocks in our Chinese sample into decile groups based on nominal prices at previous months' end,[28] and cumulative returns over past 12 months, skipping the most recent month. We construct the momentum strategy by going long in past winner stocks (above the 80th percentile) and short in past loser stocks (below the 20th percentile). We rebalance the portfolios monthly and record the equal-weighted monthly returns.[29] The first row of numbers in Table 3 presents the results. For all stocks regardless of nominal price levels, the momentum strategy generates an insignificant return of 0.212% in China (t-value = 0.82). This is consistent with the finding in Chui, Titman, and Wei (2010).

In contrast, among the highest-priced stocks (the tenth decile based on nominal prices), the momentum strategy generates a significant return of 1.662% per month (t-value = 4.00). The economic magnitude suggests an annualized return of 19.94%. This result confirms our conjecture that decreasing (increasing) the fraction of small investors strengthens (weakens) momentum returns.[30]

---

[28] Lagging the nominal price one more period does not materially alter the results.

[29] Value-weighting leads to similar results with somewhat diminished magnitudes; these results are available on request.

[30] A standard limits-to-arbitrage argument to explain more momentum in high-priced stocks presents challenges because in untabulated results, we find that turnover, a proxy for liquidity is higher in the high-priced stocks. Further, the Amihud (2002) measure of liquidity does not show appreciable variation across price-based deciles. Grinblatt and Han (2005) propose a theory of

[Insert Table 3]

[Insert Figure 4]

Figure 4 shows the cumulative returns from the momentum strategy for the highest-priced stocks in China, in comparison with the momentum strategy using all stocks. Starting with one yuan at the beginning of January 2000, the high-price momentum strategy conditional on the top decile group accrues over 30 yuan by the end of 2020.[31] The overall momentum strategy, however, generates a return that is one-fifth of that in the high-priced stocks.

Moreover, when comparing returns from the momentum strategy across different price-based groups, we find that the marginal effect decreases as we move from high- to low-price groups. For example, the average return goes from 1.662% in the tenth decile, to 0.732% in the ninth decile, and to 0.072% in the lowest-price decile. Upon using the Fama and French five-factor model to adjust for risk, the monthly alpha is 1.771% (*t*-value =4.12) in the tenth decile, and -0.027% in the first decile.[32] Hence, there is no evidence that risk drives the higher momentum profits in high-priced stocks. Further, the risk-adjusted difference in momentum profits across the extreme price-based decile amounts to 1.591% per month and is statistically significant. The difference is also significant if we consider only stocks with above-median stock prices. In this case, the

---

momentum based on the disposition effect, wherein stocks with high gains represent undervaluation due to the eagerness to sell winners. However, Birru (2015) argues that momentum is preserved after stock splits, even the disposition effect disappears post-split because of a failure to update reference prices. We show a similar effect for China within Section 5.

[31] To exclude the impact of the Covid-19 pandemic on the results, we replicate our analysis by omitting the 2020 observations and find similar results.

[32] We use the data on the five Fama and French factors from CSMAR, which follows the method of Fama and French (2015). We also reconstruct the factors ourselves, and get quantitatively similar results.

corresponding risk-adjusted difference (between the top and fifth deciles) is 1.456% per month and continues to be significant.

There may be a residual concern that high nominal prices proxy for high past performance that pushes up stock prices. To alleviate this concern, we first sort stocks into deciles based on nominal prices, and then sort them into quintiles based on past cumulative returns. The momentum strategy with this sequential sort generates similar results as Table 3. For example, the average return among highest-priced stocks is 1.435% (t-value = 3.71). These results are reported in Appendix A, Table A.2.[33]

To sum up, the results present strong evidence that (i) there is no discernible momentum overall, and (ii) there is statistically and economically significant momentum in high-priced stocks within the Chinese market. This evidence dovetails with our findings in Section 3 that small investors avoid high-priced stocks, and prefer low-priced stocks. Thus, the findings confirm the notion that small retail investors, that mainly populate the clientele for low-priced stocks, attenuate momentum, whereas relatively sophisticated investors contribute to momentum.

4.2 Short-term reversals

Recall that as per our working hypothesis, the noise trades of small, retail investors should contribute to reversals (Nagel 2012). To investigate this issue, we document profits from short-term (monthly) reversals in China in Table 3.

[33] In another test, we also consider the winner and loser profits separately, and find that the higher momentum in high priced stocks is a symmetric phenomenon; winners earn higher profits and losers earn lower profits in high-priced stocks relative to low-priced ones. Further, there is no evidence that low-priced stocks experience reversals, mitigating the concern raised by Daniel and Moskowtiz (2016) that the reversal of extreme losers attenuates momentum profits. These findings confirm that momentum in high-priced stocks is not due to nominal prices proxying for past performance. Results are available on request.

We find that the pattern of reversal profits is in the opposite direction to Panel A. Specifically, reversal profits are highest (in absolute terms) in the bottom price decile, whereas they are insignificant in the top price decile (-1.950% vs. -0.319%). The difference in risk-adjusted reversal profits across the extreme price-based deciles is 1.591% per month and is statistically significant. The difference continues to be significant if we restrict our attention to stocks with above-median nominal prices. This evidence supports our initial conjecture that retail investors contribute to inventory-induced reversals via their noise trades.

Of course, it is possible that low prices might be associated with high illiquidity, which could exacerbate short-term reversals (Avramov, Chordia, and Goyal 2006). We address this issue in two ways. First, to specifically bring out the role of retail investors, we sort stocks into deciles by net buying pressure[34] of small investors in month t, and measure the returns on these deciles in month t+1. We find that reversal profits in the decile with the highest buying pressure exceed that in the lowest one by 0.659% per month, and this difference is statistically significant at the 1% level. This confirms the role of retail investors in short-term reversals.

Next, to further ascertain the role of illiquidity, we sequentially sort stocks into quintiles by the Amihud (2002) measure of illiquidity, and then by the stock price at the end of month t, and measure returns on these portfolios in month t+1. The reversal profits for these 25 portfolios are presented in Table A.3. As can be seen, these profits are higher in low-priced stocks within four of five illiquidity quintiles. The difference in reversal profits across low- versus high-priced stocks is significant at the 5% level in these cases. Overall, these findings point to the impact of nominal stock price on reversal profits beyond the effect of illiquidity.

[34] The net buying pressure is defined as (B-S)/(B+S), where B (S) is the yuan quantity purchased (sold) by investors during a given period.

All of the above evidence together implies that small investors play an important role in generating short-term reversals. Hence, the evidence accords with the notion that short-horizon retail investors influence short-term reversals (Nagel 2012; Sias and Starks 1997).

4.3 Fama-MacBeth regressions

The portfolio analyses of the previous sections do not account for other determinants of average returns. Accordingly, we now use Fama and MacBeth (1973) (FM) regressions to corroborate how the momentum effect is impacted by nominal prices in China, while controlling for a variety of stock characteristics. The regressions are estimated at the monthly frequency as

$$\begin{aligned} R_{i,t+1} = \alpha_t + \beta_1 MOM_{i,t} + \beta_2 High\,price_{i,t} + \beta_3 High\,price_{i,t} * MOM_{i,t} \\ + \gamma_i Control_{i,t} + \varepsilon_{i,t}, \end{aligned} \quad (2)$$

where $MOM_{i,t}$ denotes the cumulative return of stock *i* from month *t*-11 to month *t*-1. *High price* is a dummy variable that equals one if the price is in the top price quintile and zero otherwise. Control variables include book-to-market, gross profitability, size, asset growth, and the lagged one-month return. The momentum variable as well as the control variables are standardized each month to have zero mean and unit standard deviation.

We present the regression results in Table 4.

[Insert Table 4]

Column (1) only contains *MOM*, and its coefficient is 0.035 and statistically insignificant (*t*-value = 0.42). This indicates that the momentum effect is not present on aggregate in the Chinese stock market, which is consistent with the portfolio sort results in Table 3. To examine whether the momentum effect varies with stock price, column (2) includes the interaction term between *MOM* and

High price. The coefficient on the interaction term is 0.230 with a *t*-value of 3.57, thereby indicating that the momentum effect exists among high-priced stocks. The coefficient on *High price* by itself is statistically insignificant, suggesting that high nominal prices themselves do not predict stock returns after controlling for key stock characteristics.

We further examine whether other variables subsume the momentum effect among high-priced stocks. First, we look at short- and long-term reversals. The notation *STR* stands for the prior 1-month return and *LTR* stands for the prior 5-year return excluding the most recent year. Column (3) shows that controlling for *STR* weakens the momentum effect; the coefficient on the interaction of *MOM* with *High price* decreases to 0.204 (*t*-value = 3.25). Consistent with Table 3 that high prices weaken the short-term reversal effect, the coefficient on the interaction of *STR* with *High price* is 0.210 (*t*-value = 3.02). Column (4) shows that *LTR* does not vary with stock price and its interaction with *High price* is not significant.

If the number of shares outstanding does not vary much in the cross-section, the high-price effect on momentum would be equivalent to a firm size effect (Fama and French 2012). To ascertain whether this is the case, we include market capitalization as of the end of the previous month as a control in Table 4. Column (5) shows that the interaction of firm size with *MOM* only partially weakens the high price effect. Therefore, price exerts an effect over and beyond that of market capitalization.

Next, in a comprehensive study, Goyal, Jegadeesh, and Subrahmanyan (2022) find that underreaction is the most sensible explanation for momentum. Columns (6) and (7) consider two proxies for underreaction: the 52-week high variable in George and Hwang (2004) and the frog-in-the-pan (*FIP*) variable in

Da, Gurun, and Warachka (2014).[35] The results are mixed; controlling for the 52-week high attenuates the high price effect, whereas controlling for *FIP* has no impact. Finally, we include the percentage of outstanding shares held by institutional investors,[36] and find that it is the most robust explanatory characteristic in explaining the high-price momentum effect, relative to the other characteristics we consider. The coefficient on the interaction of *MOM* with *High price* attenuates to 0.137 (t-value = 2.24) in this case. This finding supports the role of quasi-rational (sophisticated) traders such as institutions in momentum. We revisit the role of institutions in Section 4.5 below.[37]

Overall, the results from the FM regressions confirm a strong momentum effect among high-priced stocks. This finding supports our main hypothesis: the momentum effect statistically exists (disappears) when participation by small retail investors is low (high).

4.4 Retail investors and momentum: U.S. vs. China

The immediate question that arises from Section 4.1 is that of how our findings relate to the U.S. context. Accordingly, we now consider the relation between nominal price and momentum profits in the U.S. Our hypothesis is that small retail investors (which tend to be more active in low-priced stocks) cause reversals which offset momentum caused by underreaction of quasi-rational informed traders, such as institutions, to cash flow signals. This reasoning

---

[35] The 52-week high variable is the ratio of the stock price at the end of the previous month to its highest price over the previous 12 months. The *FIP* variable equals $sgn(MOM) \times (\%neg - \%pos)$, where *%pos* and *%neg* are the percentages of daily returns that are positive and negative, respectively, over the period across which *MOM* is measured.

[36] Institutions, according to CSMAR, include funds, QFII, brokers, insurance companies, security funds, trusts, finance and non-finance companies, banks, and other.

[37] Since some of the variables in Table 4 are highly correlated (such as size, institutional holdings, and price), to avoid misleading inferences, we do not present all of them in the same regression. In unreported results, the interaction of institutions with *MOM* remains significant when we do include all of them, but nothing else is significant.

suggests that in an economy where institutions dominate retail investors, there would not only be stronger momentum, but the relation between momentum and price levels would be weaker.[38] The latter is because in such an economy, retail trading activity might not dominate that of institutions in *any* price-sorted portfolio, thus obscuring the cross-sectional relation between momentum and price.

Our tests confirm the above conjectures: First, the ratio of median institutional holdings in the extreme (high vs. low) deciles of price-sorted portfolios is 7.40 in China and 3.11 in the USA over the 2000-2020 period.[39] This indicates more homogeneity in institutional holdings in the U.S. vs. China across price-sorted groups. Next, in an exact U.S. analog of Table 3, we find a risk-adjusted momentum profit differential between the extreme high- and low-price deciles of -0.44% per month (less than one-third that in Table 3, and of the reverse sign), with a modest *t*-statistic of -1.83.[40] Thus, in the U.S., where retail investors are less dominant, there is no evidence of a positive relation between momentum and price.[41]

---

[38] Indeed, the proportion of volume from retail investors is much smaller in the U.S. For example, Jones et al. (2022) indicate that as high as 85% of volume on the Shanghai Stock Exchange emanated from retail investors in 2020, whereas the corresponding number for Russell 3000 stocks is only about 10% (for the latter, see Factbox: The U.S. retail trading frenzy in numbers. "Reuters, U.S. Legal News'' by John McCrank (1/29/2021)). Ideally, one would like to compute a price-based constraint for retail investors in the U.S. (analogous to that in Table 1) but retail trading data is not available for the U.S. for any period over the past two decades.

[39] Institutional holdings across nominal price deciles (low to high) in fact range from 0.99% to 7.3% and 24.39% to 75.7% in China and the U.S., respectively. Chinese institutions include funds, QFII, brokers, insurance companies, security funds, trusts, finance and non-finance companies, banks, and other miscellaneous categories, according to CSMAR. US institutional holdings are the aggregated holdings of all investors in the 13(f) database.

[40] This finding is suggestive that we are picking up some sort of bias in our result linking momentum and nominal price; as it is highly likely such biases should show up both in the U.S. and China.

[41] Institutional holdings are modest prior to the 1990s in the U.S., and so is retail turnover (Blume and Keim 2012). However, our arguments rely on a tension between small retail traders and quasi-rational sophisticated investors, of which institutions are but one type. That there is strong

We also investigate another, more important, reason for the contrast between the U.S. and China which has to do with the *enforcement* of the roundlot rule across the two countries. Using the discount brokerage data of Terrance Odean over the 1991-1996 period, we calculate percentiles of the average number of shares held by investors. We identify small (large) investors as those with average portfolio sizes below (above) $90k ($240k).[42] We find that for small investors, the 10th percentile is 92 shares, indicating that the roundlot rule is not strict, unlike for China (viz. fourth row of Table 1). To investigate this issue further, we define a trade as subject to a roundlot rule if the shares traded are divisible by 100. We find that only 81.5% of trades are subject to a roundlot rule. We then look at the average and median transaction prices conditional on roundlot trades. The average (median) price for roundlot trades is 26.8 (21.3) whereas that for non-roundlot trades is 50.0 (33.5). This suggests that when prices are high, brokers exempt investors from roundlot rules, effectively loosening the price constraint. The lack of an identifiable price constraint accords with the lack of a relation between nominal price and momentum in the U.S.

We have observed above that since the roundlot restriction is not strictly imposed on U.S. investors, price is not the ideal identifying variable for retail participation. We therefore use two other methods to measure U.S. retail participation. Our first approach uses the results of Kumar (2009), who shows that retail investors prefer stocks with high past volatility and skewness, since these are characteristics of lotteries.[43] We apply his approach to stratify common

---

and discernible momentum in the U.S. prior to the 1990s (Jegadeesh and Titman 1993) indicates that the net effect of underreaction to fundamentals by quasi-rational non-institutional investors dominates the effect of small investors' noise trading.

[42] These thresholds are established to keep the ratios of the cutoffs to per capita income the same in both countries.

[43] Skewness and volatility might be positively related to risk, including downside, or crash, risk. (Chen, Hong, and Stein 2001). However, under the traditional assumption of risk aversion, there

stocks listed in NYSE, Nasdaq and AMEX into lottery and non-lottery. We also use the method of Bali, Cakici, and Whitelaw (2011) to define lottery stocks (via the maximum return achieved by the stock in the current month). We then perform Fama-MacBeth regressions of one month ahead returns on the Table 4 controls, as well as the lottery dummy, *MOM*, and the interaction of the two. We present the results in the two panels of Table A.4. As can be seen, in each case, there is a clear indication that momentum is attenuated in stocks for which retail investors have a proclivity. Specifically, the interaction of momentum with the lottery dummy is negative and strongly significant, with an absolute *t*-statistic that exceeds 4. This result is consistent with the notion that retail participation attenuates momentum.

The next question is whether a relation between lottery stocks and momentum exists in China. On this issue, note that momentum in China exists *only* in the high-priced stocks, where small retail investors' participation is low to begin with (Panel B of Table 1). The low baseline level of retail participation in high-priced stocks, and because momentum prevails mainly in this smaller cross-section, indicate that it may be challenging to obtain a statistically strong relation between the lottery status of stocks and momentum. In other words, we would not expect the analog of Table A.4 in China to be as clear-cut. Consistent with this observation, in untabulated results we find that the interaction dummy in China for the corresponding Table A.4 regression is negative, but not statistically significant.

In concluding this subsection, our overarching observation is the following. Price is a strong identifying variable for retail participation in China due to the strict imposition of the roundlot rule. This is not the case in the U.S. where

is no reason why retail investors should be *attracted* to such high-risk stocks, and lottery preferences form a plausible alternative, as Kumar (2009) points out.

enforcement of the roundlot rule is uneven. Accordingly, nominal price is strongly related to momentum in China but not so in the U.S. Having addressed the implications of our analysis for China and the U.S., for the remainder of the paper, we revert back to the Chinese market, where there is clearer identification of participation by small retail investors, due to the strict imposition of the roundlot rule.

5. A further look at momentum in Chinese high-priced stocks

The earlier sections reliably establish the existence of momentum in stocks with high nominal prices within China. Our hypothesis is that this momentum is due to quasi-rational but sophisticated investors, and institutions are prime candidates for such investors. To investigate the validity of this hypothesis, in Table 5, we consider a variety of momentum determinants in high-priced stocks; with one of them being institutional holdings. As in Goyal, Jegadeesh, and Subrahmanyam (2022) (GJS hereafter), we run regressions of the form

$$R_{i,t+1} = \alpha_t + \beta_1 MOM_{i,t} + \beta_2 X_{i,t} + \beta_3 X_{i,t} * MOM_{i,t} + \gamma_i Control_{i,t} + \varepsilon_{i,t}, \qquad (3)$$

where X is, in turn, book-to-market, residual analyst coverage, analysts' revisions, turnover, 52-week high, *FIP*, return volatility, and institutional holdings.[44] The FM regressions are run *only* for the high-priced stocks, and the control variables are the same as those in Table 4.

[Insert Table 5]

Table 5 reports the results, with and without controls. We find that several X variables are associated with returns. In particular, while analysts' revisions

[44] The detailed motivation and calculation methods for all but two of these variables are provided in GJS, and are omitted here for brevity (see also Footnote 27). The variables not included in GJS are analysts' revisions and institutional holdings. The former is calculated as in Stickel (1991) and the latter is simply the proportion of the total float of a company held by institutions, as reported at the end of the most recent quarter.

mitigate momentum, revisions do not influence the strength of the momentum effect. This finding thus indicates that the momentum effect is linked to slow updating of earnings forecasts by analysts, a finding that is consistent with Chan, Jegadeesh, and Lakonishok (1996).

Turning now to the interaction terms of each of the *X* variables with *MOM*, we find that these are significant for three variables; namely, turnover, return volatility, and fund holdings. The interaction with turnover has a negative sign. As in GJS, assuming that turnover captures overconfidence (Lee and Swaminathan 2000), and noting that overconfidence is associated with more momentum (Daniel, Hirshleifer, and Subrahmanyam 1998), the negative sign for turnover is opposite to that predicted by theory. The interaction of momentum with return volatility also carries a negative sign. This finding is at odds with the notion that momentum profits are risk compensation for real options (Sagi and Seasholes 2007). Institutional holdings' interaction with momentum, however, is the most robustly significant variable, and carries a positive sign. Noting that retail investors prefer highly volatile stocks (Kumar 2009), and the evidence that institutional underreaction influences momentum (Chui, Subrahmanyam, and Titman 2022),[45] the finding thus accords with smaller retail investors detracting from momentum, and institutional investors contributing to momentum.

In Figure 5, we plot the momentum profits over time for only the high-priced stocks, by quintiles sorted by institutional holdings.

[Insert Figure 5]

[45] See also Lou (2012) and Vayanos and Woolley (2013). Lou, Polk, and Skouras (2019) and Bogousslavsky (2021) provide evidence consistent with the view that institutions underreact to overnight information.

The figure demonstrates that investing one unit in the highest holdings quintile at the beginning of the sample multiplies it by a factor of nine by sample-end, whereas the cumulative return from investing in the lowest holdings quintile is close to zero. In untabulated results, we verify that this difference is significant at the 1% level. This finding confirms the role of institutions in causing momentum within high-priced stocks.

6. Identification via stock split events

So far, we have used nominal prices to proxy for the cross-sectional variation in the fraction of small investors in stocks. However, even though we include a battery of control characteristics, and control for risk, one may yet be concerned that nominal price may be correlated with other stock characteristics, either observed or unobserved. To further strengthen our casual interpretation, we exploit time-series changes in nominal prices caused by stock split events. Since splits mechanically lower nominal prices, they make the stocks more affordable to small investors,[46] so that they should increase participation by such investors and mitigate momentum.

We obtain stock split data for Chinese A-shares from the CSMAR database for the period 2000 to 2020. We start with a sample of 43,085 stock split announcements after 2000, for which the underlying firms have complete accounting information and at least one year of prior stock returns included in the CSMAR database. We only use three types of splits in our main analysis, which are stock dividends, rights offerings, and split shares. We also screen out stock splits with split ratios less than 0.1 to ensure material price changes after

[46] Other recent papers use stock split events as quasi-exogenous shocks to study hypotheses on irrational behavior that is related to nominal prices (Birru 2015; Birru and Wang 2016; Shue and Townsend 2021). The basic premise behind these studies is that changes in nominal prices on pre-announced stock split dates are not related to firm fundamentals.

stock splits. Our final sample consists of 9,901 stock splits after implementing these screens.

Before proceeding to the tests, we need to discuss two caveats surrounding stock split events. First, splits are endogenously determined by firms; for example, firms may use such events to attract retail investors via low prices and thus build liquidity (Titman, Wei, and Zhao 2022).[47] Second, stock split events may play an attention-grabbing role for retail investors. Specifically, to the extent that investors have limited attention, the announcement of stock splits can draw investors' attention and thus induce them to trade these stocks (Barber and Odean 2008; Titman, Wei, and Zhao 2022).

Regarding the concerns mentioned above, we make three observations. First, as per Titman, Wei, and Zhao (2022), insider-motivated, manipulative split events are more likely to occur in low-priced stocks, whereas the events of our focus are in high-priced stocks. Second, the financial constraint channel offers its own distinct predictions regarding heterogeneity in the impact of splits on investor participation. Specifically, the increasing effect on investor participation should be more pronounced among small investors than among large investors because small investors have tighter financial constraints than large ones. Further, the effect should be stronger for splits with higher split ratios, ceteris paribus, because higher split ratios lead to lower after-split prices. The implications are unique to the financial constraints channel because it is not obvious why a higher split ratio should be more attention-grabbing than a low one, and why attention-

[47] There are other motives of fund managers in announcing stock splits, for example, signaling firm value (Grinblatt, Masulis, and Titman 1984; Brennan and Copeland 1988; Almazan, Banerji, and Motta 2008), earnings management (Chan, Li, and Lin 2019), moving the effective tick size to an optimal level (Angel 1997; Schultz 2000), and aiming for improvements in liquidity (Lin, Singh, and Yu 2009).

grabbing should play a bigger role for smaller investors.[48] Finally, it is hard to attribute the inverse relation between splits and momentum (our principal focus) to managerial motives. Specifically, there is no obvious reason why the motivation to split would be *enhanced* by the additional noise trading due to additional entry of retail investors, which is what attenuates momentum.

6.1 Stock splits and investor participation

We now conduct event studies examining changes in investor participation around stock splits. To this end, we estimate the following regression:

$$Participation\_propensity_{i,t} = \alpha + \sum_{k=-5}^{6} \beta_k 1\left(EventMonth_{i,t} = k\right) + \tau_t + \nu_i + \varepsilon_{i,t} \quad (4)$$

where $Participation\_propensity$ is the log number of investors, among either the small or large investor groups, who hold stock i at the end of month t, $1\left(EventMonth_{i,t} = k\right)$ are indicator variables that equal unity if month t is k months before or after a split month for stock i, τ_t are calendar year-month fixed effects, and ν_i are stock fixed effects. Observations are at the stock-month level, and the sample is limited to the six months before and the six months after a split. The coefficients β_k measure the difference in investor participation in event month k relative to month $t-6$, the omitted category. Since investor holdings data are from 2016 to 2020, we use 1,797 (out of the total of 9,901) stock split events in this part of the analysis, of which 857 are of high-priced stocks.

[Insert Figure 6]

[48] Cui et al. (2022) provide a behavioral model of stock splits which predicts strong split announcement returns when split ratios are high. However, their paper does not predict our result of lower momentum following splits. Hence, the two papers are complementary.

Figure 6 shows time-series patterns for participation propensities across different investor groups around stock split events. We find that for the small investor group, there is an immediate and persistent jump in stock participation after splits in high-priced stocks. In contrast, there is no discernible jump in investor participation among large investors, which is consistent with the prediction based on the financial constraint channel. [49]

[Insert Table 6]

We next estimate the following regression to estimate economic magnitudes of changes in participation:

$$Participation\ propensity_{i,t} = \alpha + \beta_1 After_{i,t} + \tau_t + \nu_i + \varepsilon_{i,t}, \quad (5)$$

where *After* is a dummy variable that is unity in the post-split period, and zero otherwise. The regression also includes stock and year-month fixed effects. Standard errors are double-clustered by stock and year-month. Table 6 shows the results. In column (1), the coefficient estimate of *After* for small investors is 0.229 (t-value = 5.67). In contrast, the estimate for large investors, in column (4), is only 0.102 (t-value = 2.93). As for economic magnitudes, high-priced stock splits lead to a 25.7% increase in small investor participation, and to only a 10.7% increase in larger investors' participation. The results hold when we include both year-month and stock fixed effects, as shown in columns (2) and (5).

To further distinguish the financial constraint hypothesis from alternative hypotheses, we use the split ratio as the mediating variable. The intuition is that under the financial constraint hypothesis, a higher split ratio leads to lower after-

---

[49] Titman, Wei, and Zhao (2022) show that investors with account values less than 5M yuan are attracted to stock splits. We define small/large investors based on their heterogeneous susceptibility to financial constraints. Our results based on finer classifications do not necessarily contradict with theirs.

split stock prices, and, as a result, induces more participation from small investors. On the other hand, there is no clear reason to believe that split ratios are associated with firms' manipulation motives or/and investor attention. In columns (3) and (6), we add the interaction terms between *After* and the split ratio. Consistent with our predictions, the coefficient estimates on the interactions are all positive and the estimate is about four times higher for small investors than for larger investors (0.298 versus 0.072). We conclude that stock splits increase the net fraction of small investors in the high-priced stock group.

In Table 6 Panel B, we run regressions for non-high-priced stock splits (Quintiles 1 to 4). We find similar results in that after splits, the number of small investors investing in these stocks increases by higher percentages than the number of large investors (18.5% versus 10.7%). We find, however, that the corresponding increase for large investors is also statistically significant, suggesting that investors' heightened attention may also contribute to more retail investor participation after stock splits. All in all, the results show that small investors increase their participation in stocks post-split, and that this effect is most likely due to the financial constraint channel, especially for high-priced stocks.

6.2 Stock splits and momentum

Our analysis also predicts that any event that stimulates the entry of small investors into a stock would weaken the existing momentum effect. To test this, we define a stock-level momentum indicator (*I_MOM*) which is unity if the stock's past 12-month return is above (or below) the cross-sectional median and its current month's return is also above (or below) the corresponding median[50] We run regressions analogous to equations (4) and (5):

$$I\_MOM_{i,t} = \alpha + \sum_{k=-5}^{6} \beta_k 1\big(EventMonth_{i,t} = k\big) + \tau_t + \nu_i + \varepsilon_{i,t}, \tag{6}$$

$$I\_MOM_{i,t} = \alpha + \beta_1 After_{i,t} + \tau_t + \nu_i + \varepsilon_{i,t}. \tag{7}$$

Figure 7 plots the regression coefficients from equation (6) and shows that there is a sharp and abrupt decline in stock-level momentum following splits within the high-priced stock group.[51] This is consistent with the view that a net increase in the fraction of small investors decreases the momentum effect.

[Insert Figure 7]

[Insert Table 7]

We report regression estimates of equation (7) in Table 7. Column (1) shows that for the high-priced stock group, stock splits weaken stock-level momentum by 6.3% after the split. The result survives after we control for stock and year-month fixed effects in column (2). In column (3) when we include the interaction term with the split ratio, we find a strengthened result when split ratios are higher. In untabulated regressions, we exclude the suspicious splits identified by Titman, Wei, and Zhao (2022)[52] and still find robust results. Overall, these findings confirm that splits, which stimulate the participation of retail investors, are followed by decreased return momentum.

[50] In untabulated results, we reach similar conclusions with return cutoffs set at the 40th and 60th percentiles.

[51] Of course, stocks are more likely to split after price rises. This observation does not imply a sharp attenuation in momentum post-split (i.e., an abrupt decrease in the tendency for both current and past returns to be high after the split, particularly for high split ratios), as shown in Figure 7 and Table 7.

[52] These splits are characterized by insiders' lockup expirations near to the split date, high accounting accruals, and negative pre-announcement performance, so that they signify manipulative motives.

7. Conclusion

We explore the link between investor clientele and momentum via identification strategies in Chinese shares. We utilize the observation that a strictly-enforced roundlot (100-share minimum) rule places a participation constraint on small investors. Using retail account data we show that small retail investors indeed have a lower presence in high-priced stocks, and that such investors avoid high-priced stocks because financial constraints bind more strictly in such stocks.

We conduct asset pricing tests using nominal prices as a quasi-exogenous proxy for retail investor participation. We find that while there is no momentum on aggregate in the Chinese market, there is significant momentum in high-priced stocks. We also find that short-term reversals are strongest in lowest-priced stocks and weakest in highest-priced stocks, a pattern that is opposite to that for momentum. Momentum in the high-priced group is strongest for stocks held relatively more by institutions. We also find that small investors' participation increases and momentum profits decrease after splits in high-priced stocks. Thus, overall the results paint a picture that institutions contribute to momentum, and retail investors attenuate momentum but contribute to reversals.

We believe that our use of nominal prices to (inversely) measure retail participation can also speak to the question of how the presence of small investors impacts other asset pricing phenomena. Thus, the role of small investors in anomalies related to gross profits, accruals, and real investment would seem to be an important topic for future research.

References

Akbas, F., Boehmer, E., Jiang, C., & Koch, P. D. (2022). Overnight returns, daytime reversals, and future stock returns. *Journal of Financial Economics*, 145(3), 850-875.

Almazan, A., Banerji, S., & Motta, A. D. (2008). Attracting attention: Cheap managerial talk and costly market monitoring. *Journal of Finance*, 63(3), 1399–1436.

Amihud, Y. (2002). Illiquidity and stock returns: Cross-section and time-series effects. *Journal of Financial Markets*, 5(1), 31-56.

Andrei, D., & Cujean, J. (2017). Information percolation, momentum and reversal. *Journal of Financial Economics*, 123(3), 617–645.

Angel, J. J. (1997). Tick size, share prices, and stock splits. *Journal of Finance*, 52(2), 655–681.

Avramov, D., Chordia, T., & Goyal, A. (2006). Liquidity and autocorrelations in individual stock returns. *Journal of Finance*, 61(5), 2365-2394.

Bali, T. G., Cakici, N., & Whitelaw, R. F. (2011). Maxing out: Stocks as lotteries and the cross-section of expected returns. *Journal of Financial Economics*, 99(2), 427-446.

Barber, B. M., Huang, X., Odean, T., & Schwarz, C. (2022). Attention induced trading and returns: Evidence from Robinhood users. *Journal of Finance,* 77(6), 3141-3190.

Barber, B. M., Lee, Y.-T., Liu, Y.-J., & Odean, T. (2009). Just how much do individual investors lose by trading? *Review of Financial Studies*, 22(2), 609–632.

Barber, B. M., & Odean, T. (2008). All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors.

Review of Financial Studies, 21(2), 785–818.

Barber, B. M., Odean, T., & Zhu, N. (2008). Do retail trades move markets? *Review of Financial Studies*, 22(1), 151–186.

Barberis, N., Shleifer, A., & Vishny, R. (1998). A model of investor sentiment. *Journal of Financial Economics*, 49(3), 307–343.

Bartlett III, Robert P. (2021) Modernizing odd lot trading, *Columbia Business Law Review*, 520.

Birru, J. (2015). Confusion of confusions: a test of the disposition effect and momentum. *Review of Financial Studies*, 28(7), 1849–1873.

Birru, J., & Wang, B. (2016). Nominal price illusion. *Journal of Financial Economics*, 119(3), 578–598.

Blair, W., & Co. (2018). Why China A, why now? *Perspectives on Global Equity*, January.

Blume, M., and D. Keim, 2012, Institutional investors and stock market liquidity: Trends and relationships, *Available at SSRN #2147757*.

Boehmer, E., Jones, C.M., Zhang, X., & Zhang, X. (2021). Tracking retail investor activity. *Journal of Finance*, 76(5), 2249–2305.

Bogousslavsky, V. (2021). The cross-section of intraday and overnight returns. *Journal of Financial Economics*, 141(1), 172-194.

Brennan, M. J., & Copeland, T. E. (1988). Stock splits, stock prices, and transaction costs. *Journal of Financial Economics*, 22(1), 83–101.

Büsing, P., Mohrschladt, H., & Siedhoff, S. (2022). Decomposing Momentum: Eliminating its Crash Component. *Available at SSRN 3887512*.

Cao, J., Han, B., & Wang, Q. (2017). Institutional investment constraints and stock prices. *Journal of Financial and Quantitative Analysis*, 52(2), 465-489.

Chan, L. K., Jegadeesh, N., & Lakonishok, J. (1996). Momentum strategies. *Journal of Finance*, 51(5), 1681-1713.

Chan, K., Li, F., & Lin, T.-C. (2019). Earnings management and post-split drift. *Journal of Banking and Finance*, 101, 136–146.

Chen, T., Gao, Z., He, J., Jiang, W., & Xiong, W. (2019). Daily price limits and destructive market behavior. *Journal of Econometrics*, 208(1), 249–264.

Chen, J., Hong, H., & Stein, J. C. (2001). Forecasting crashes: Trading volume, past returns, and conditional skewness in stock prices. *Journal of Financial Economics*, 61(3), 345-381.

Chordia, T., Subrahmanyam, A., & Tong, Q. (2014). Have capital market anomalies attenuated in the recent era of high liquidity and trading activity?. *Journal of Accounting and Economics*, 58(1), 41-58.

Chui, A. C., Subrahmanyam, A., & Titman, S. (2022). Momentum, reversals, and investor clientele. *Review of Finance*, 26 (2), 217-255.

Chui, A. C., Titman, S., & Wei, K. J. (2010). Individualism and momentum around the world. *Journal of Finance*, 65(1), 361–392.

Cooper, M. J., Gutierrez Jr, R. C., & Hameed, A. (2004). Market states and momentum. *Journal of Finance*, 59(3), 1345-1365.

Cui, C., Li, F. W., Pang, J., & Xie, D. (2022). A Behavioral Signaling Explanation for Stock Splits, *Available at SSRN #4284423.*

Da, Z., Gurun, U. G., & Warachka, M. (2014). Frog in the pan: Continuous information and momentum. *Review of Financial Studies*, 27(7), 2171–2218.

Daniel, K., Hirshleifer, D., & Subrahmanyam, A. (1998). Investor psychology and security market under-and overreactions. *Journal of Finance*, 53(6), 1839–1885.

Daniel, K., & Moskowitz, T. J. (2016). Momentum crashes. *Journal of Financial Economics*, 122(2), 221-247.

Docherty, P., & Hurst, G. (2018). Investor myopia and the momentum premium across international equity markets. *Journal of Financial and Quantitative*

Analysis 53(6), 2465–2490.

Fama, E. F., & French, K. R. (1992). The cross-section of expected stock returns. *Journal of Finance*, 47(2), 427–465.

Fama, E. F., & French, K. R. (2012). Size, value, and momentum in international stock returns. *Journal of Financial Economics*, 105(3), 457–472.

Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, 116(1), 1-22.

Fama, E. F., & MacBeth, J. D. (1973). Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy*, 81(3), 607–636.

Gao, P., Hu, A., Kelly, P., Peng, C., & Zhu, N. N. (2020). Exploited by complexity. Working paper, *LSE Financial Markets Group*.

George, T. J., & Hwang, C. Y. (2004). The 52-week high and momentum investing. *Journal of Finance*, 59(5), 2145–2176.

Goetzmann, W. N., & Massa, M. (2002). Daily momentum and contrarian behavior of index fund investors. *Journal of Financial & Quantitative Analysis*, 37(3), 375–389.

Goyal, A., Jegadeesh, N, & Subrahmanyam, A. (2022). Determinants of momentum: A perspective from international data, *Available at SSRN #4012902*.

Grinblatt, M., & Han, B. (2005). Prospect theory, mental accounting, and momentum. *Journal of Financial Economics*, 78(2), 311–339.

Grinblatt, M., Titman, S., & Wermers, R. (1995). Momentum investment strategies, portfolio performance, and herding: A study of mutual fund behavior. *American Economic Review*, 85(5), 1088-1105.

Griffin, J. M., Ji, X., & Martin, J. S. (2003). Momentum investing and business cycle risk: Evidence from pole to pole. *Journal of Finance* 58(6), 2515-2547.

Grinblatt, M., & Keloharju, M. (2000). The investment behavior and performance of various investor types: a study of Finland's unique data set. *Journal of Financial Economics*, 55(1), 43–67.

Grinblatt, M. S., Masulis, R. W., & Titman, S. (1984). The valuation effects of stock splits and stock dividends. *Journal of Financial Economics*, 13(4), 461–490.

Hong, H., & Stein, J. C. (1999). A unified theory of underreaction, momentum trading, and overreaction in asset markets. *Journal of Finance*, 54(6), 2143–2184.

Hu, C., Liu, Y.-J., & Xu, X. (2021). The valuation effect of stock dividends or splits: Evidence from a catering perspective. *Journal of Empirical Finance*, 61, 163–179.

Ikenberry, D. L., & Ramnath, S. (2002). Underreaction to self-selected news events: The case of stock splits. *Review of Financial Studies*, 15(2), 489–526.

Jegadeesh, N., Luo, J., Subrahmanyam, A., & Titman, S. (2022). Momentum and short-term reversals: Theory and evidence. *Available at SSRN #4069575.*

Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *Journal of Finance*, 48(1), 65–91.

Jones, C. M., Shi, D., Zhang, X., & Zhang, X. (2022). Understanding retail investors: Evidence from China. *Available at SSRN #3628809*.

Kaniel, R., Saar, G., & Titman, S. (2008). Individual investor trading and stock returns. *Journal of Finance*, 63(1), 273–310.

Kumar, A., & Lee, C. M. (2006). Retail investor sentiment and return comovements. *Journal of Finance*, 61(5), 2451–2486.

Kumar, A., & Lim, S. S. (2008). How do decision frames influence the stock investment choices of individual investors? *Management Science*, 54(6), 1052–1064.

Kumar, A. (2009). Who gambles in the stock market? *Journal of Finance*, 64(4), 1889–1933.

Lee, C. M., & Swaminathan, B. (2000). Price momentum and trading volume. *Journal of Finance*, 55(5), 2017–2069.

Li, S., Chen, W. W., & Yu, Y. (2006). The reason for Asian overconfidence. *Journal of Psychology* 140(6), 615-618.

Li, X., Subrahmanyam, A., & Yang, X. (2021). Winners, losers, and regulators in a derivatives market bubble. *Review of Financial Studies*, 34(1), 313-350.

Lin, J.-C., Singh, A. K., & Yu, W. (2009). Stock splits, trading continuity, and the cost of equity capital. *Journal of Financial Economics*, 93(3), 474–489.

Liu, J., Stambaugh, R. F., & Yuan, Y. (2019). Size and value in China. *Journal of Financial Economics*, 134(1), 48–69.

Lou, D. (2012). A flow-based explanation for return predictability. *Review of Financial Studies*, 25(12), 3457-3489.

Lou, D., Polk, C., & Skouras, S. (2019). A tug of war: Overnight versus intraday expected returns. *Journal of Financial Economics*, 134(1), 192-213.

Nagel, S. (2012). Evaporating liquidity, *Review of Financial Studies* 25(7), 2005–2039.

Pearson, N. D., Yang, Z., & Zhang, Q. (2021). The Chinese warrants bubble: Evidence from brokerage account records. *Review of Financial Studies*, 34(1), 264–312.

Peress, J., & Schmidt, D. (2020). Glued to the TV: Distracted noise traders and stock market liquidity, *Journal of Finance* 75 (2), 1083–1133.

Sagi, J.S., & Seasholes, M.S. (2007). Firm-specific attributes and the cross-section of momentum. *Journal of Financial Economics* 84(2), 389-434.

Schultz, P. (2000). Stock splits, tick size, and sponsorship. *Journal of Finance*, 55(1), 429–450.

Shue, K., & Townsend, R. R. (2021). Can the market multiply and divide? Non-proportional thinking in financial markets. *Journal of Finance*, 76(5), 2307–

2357.

Sias, R. W., & Starks, L. T. (1997). Return autocorrelation and institutional investors. *Journal of Financial Economics*, 46(1), 103-131.

Stickel, S. E. (1991). Common stock returns surrounding earnings forecast revisions: More puzzling evidence. *Accounting Review*, 66(2), 402-416.

Titman, S., Wei, C., & Zhao, B. (2022). Corporate actions and the manipulation of retail investors in China: An analysis of stock splits. *Journal of Financial Economics*, 145(3), 762-787.

Vayanos, D., & Woolley, P. (2013). An institutional theory of momentum and reversal. *Review of Financial Studies*, 26(5), 1087-1145.

Xiong, W., & Yu, J. (2011). The Chinese warrants bubble. *American Economic Review*, 101(6), 2723–2753.

Yates, J. F., Lee, J. W., Shinotsuka, H., Patalano, A. L., & Sieck, W. R. (1998). Cross-cultural variations in probability judgment accuracy: Beyond general knowledge overconfidence? *Organizational Behavior and Human Decision Processes*, 74(2), 89-117.

Figure 1: Time series of the median stock price across price-based deciles

This figure plots median stock prices for price-based deciles between January 2000 and December 2020. The deciles are based on closing stock prices at the end of each month; Decile 10 (1) represents the highest-priced (lowest-priced) stock group.

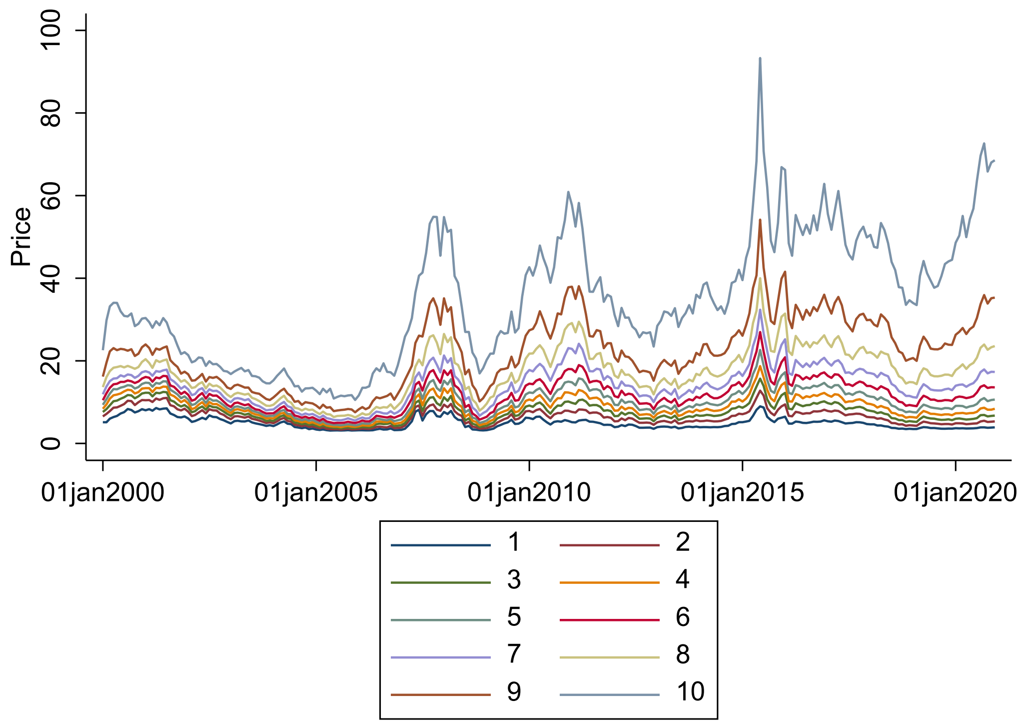
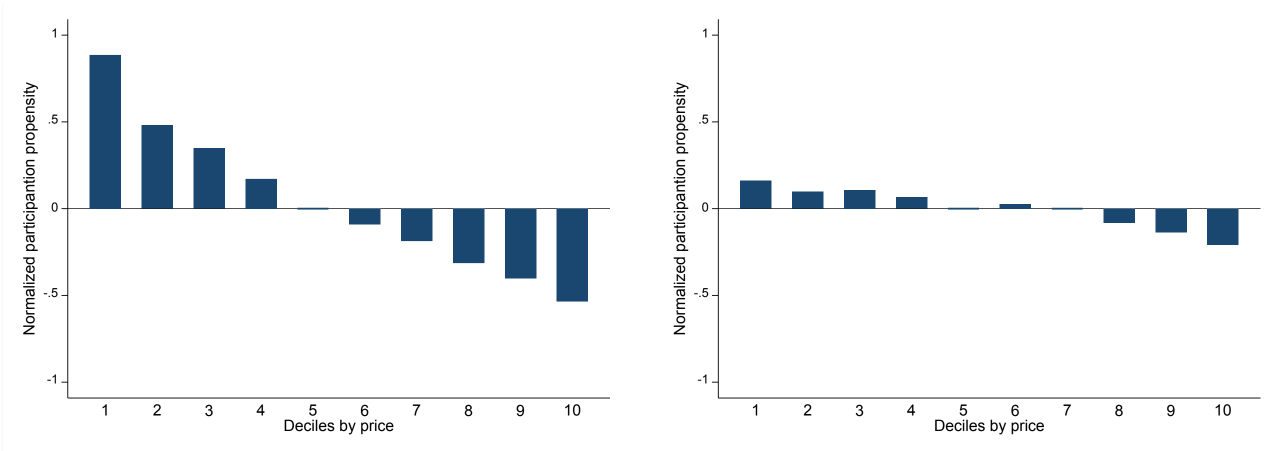


Figure 2: Participation propensity of small and large investors across price-based deciles
This figure shows the participation propensities of small and large investors, respectively, across stock price deciles. Participation propensity is the proportion of small (or large) investors who at least hold one stock in the corresponding decile group. We normalize the propensity for each investor group against the propensity for the fifth decile. Decile 10 (1) represents the highest-priced (lowest-priced) stock group.

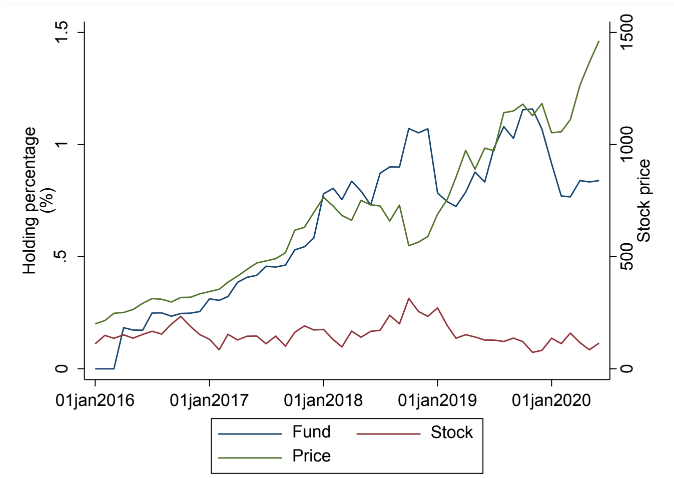


Small investors Large investors

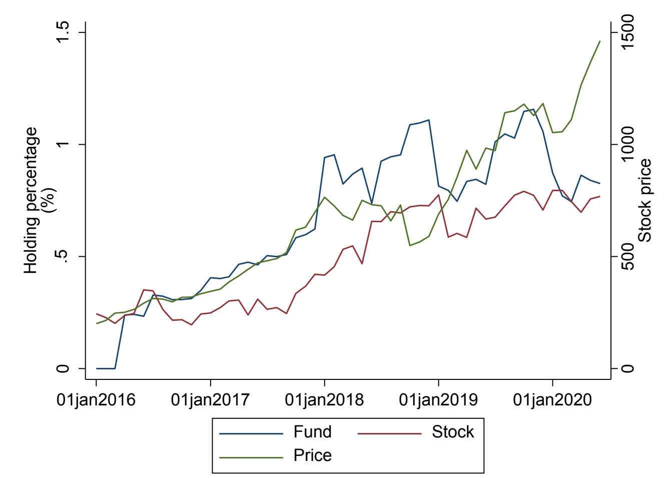
Figure 3: Portfolio weights of high-priced stocks via stocks and funds

The figure shows the time series of the average portfolio weight among small (or large) investors of high-priced stocks based on individual stock holdings and mutual fund holdings from 2016 to 2020. Panel A considers a single stock, Moutai, and also plots the time series of the stock price. Panels B and C consider groups of stocks with price higher than 100 and 50, respectively. "Stock" ("Fund") corresponds to the average portfolio weight of the stock(s) being considered based on investors' direct stock (fund) holdings. For funds, we only consider the holdings of stocks that are among the top ten holdings of the funds. The holdings are disclosed quarterly. Small (large) investors are those whose average portfolio size is below 200k (above 500k) yuan.

Panel A. Moutai

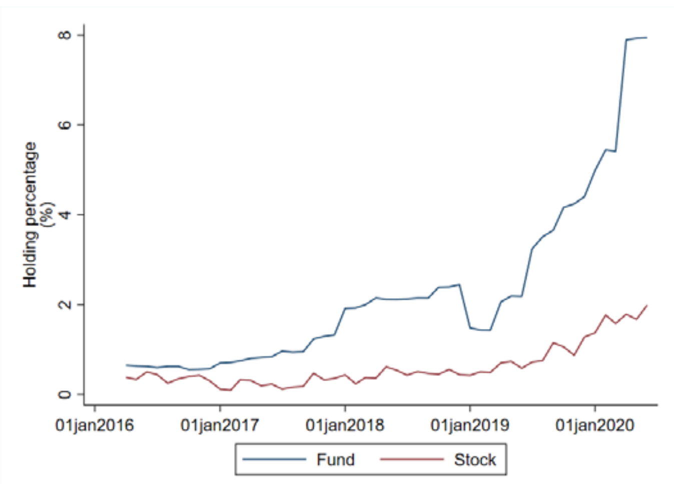


Small investors

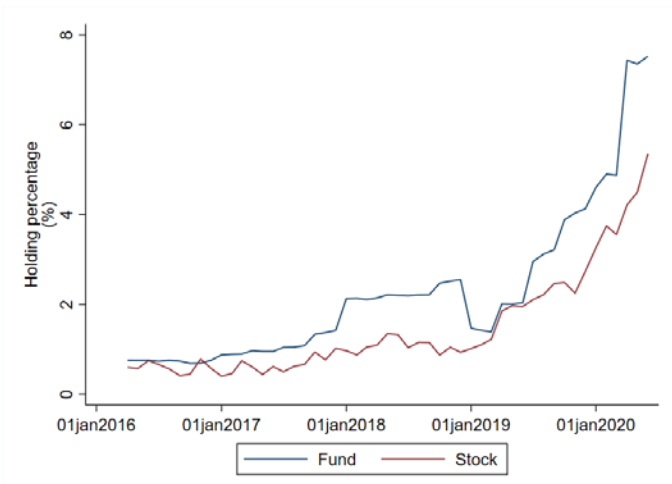


Large investors

Panel B. Stocks with price higher than 100 yuan



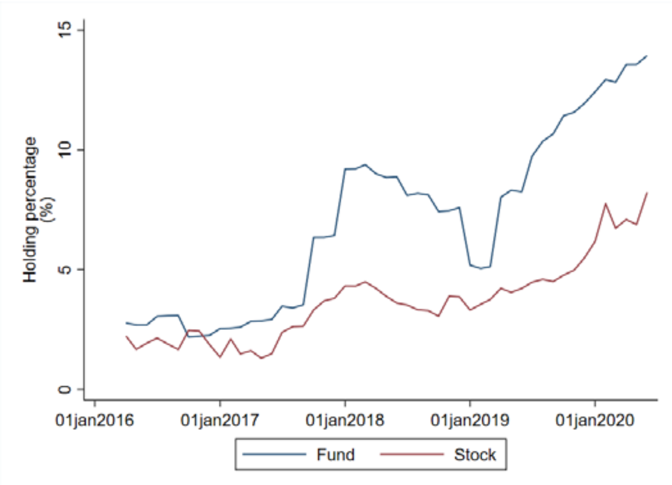
Small investors



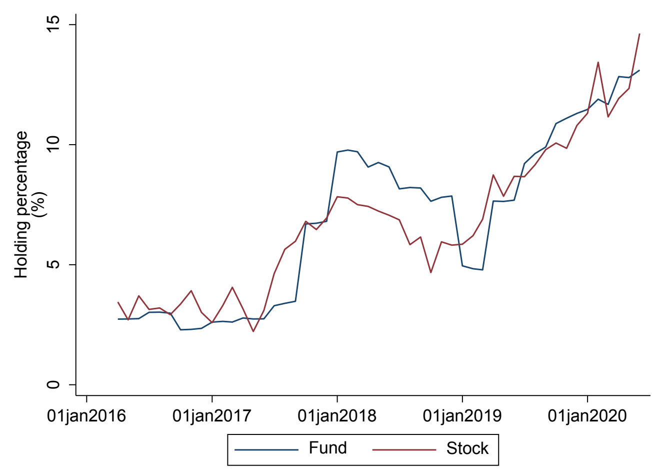
Large investors

Figure 3, contd.

Panel C. Stocks with price higher than 50 yuan



Small investors



Large investors

Figure 4: Cumulative returns of momentum strategies

The figure plots cumulative returns of momentum strategies from 2000 to 2020 when one yuan is invested in each strategy at the beginning of the sample. The blue line represents the unconditional momentum strategy for all stocks, and the red line represents the momentum strategy for high-priced stocks (Decile 10). The momentum portfolios are formed by going long the winner stocks (the top quintile) and short the loser stocks (the bottom quintile).

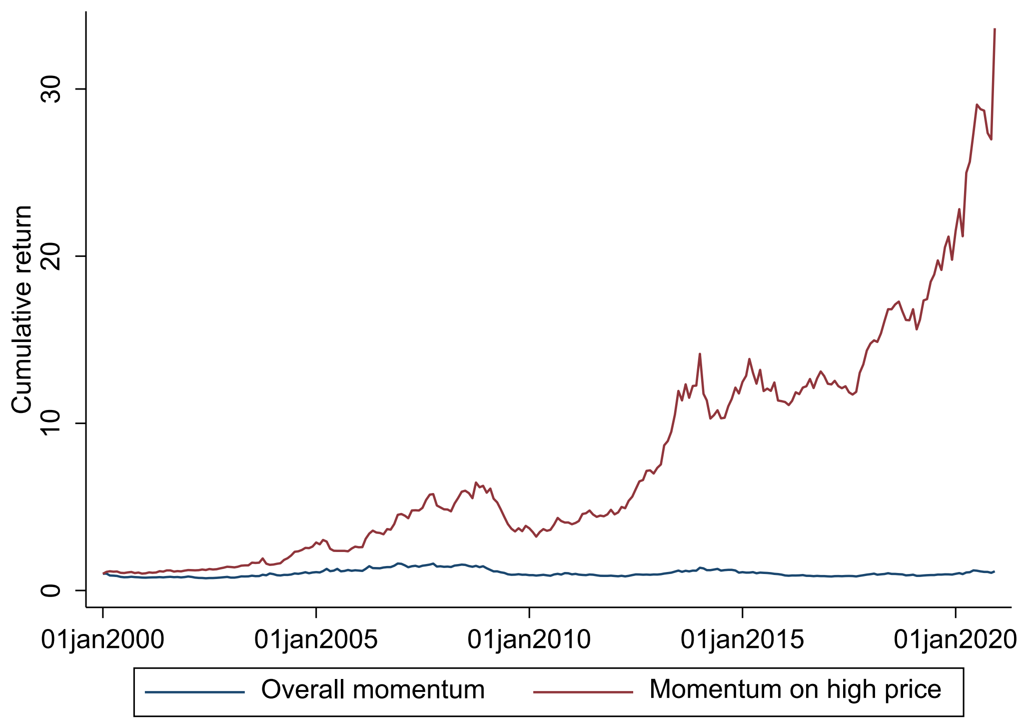


Figure 5: Cumulative returns of high-priced momentum strategies across institutional holding quintiles

This figure plots the time series of cumulative returns of the high-priced momentum strategies across institutional holding quintiles. High-priced stocks (top price quintile) are sequentially sorted into quintiles based on institutional holding and the momentum variable. The momentum strategy within each institutional holding quintile is formed by buying winners and selling losers, and rebalanced monthly.

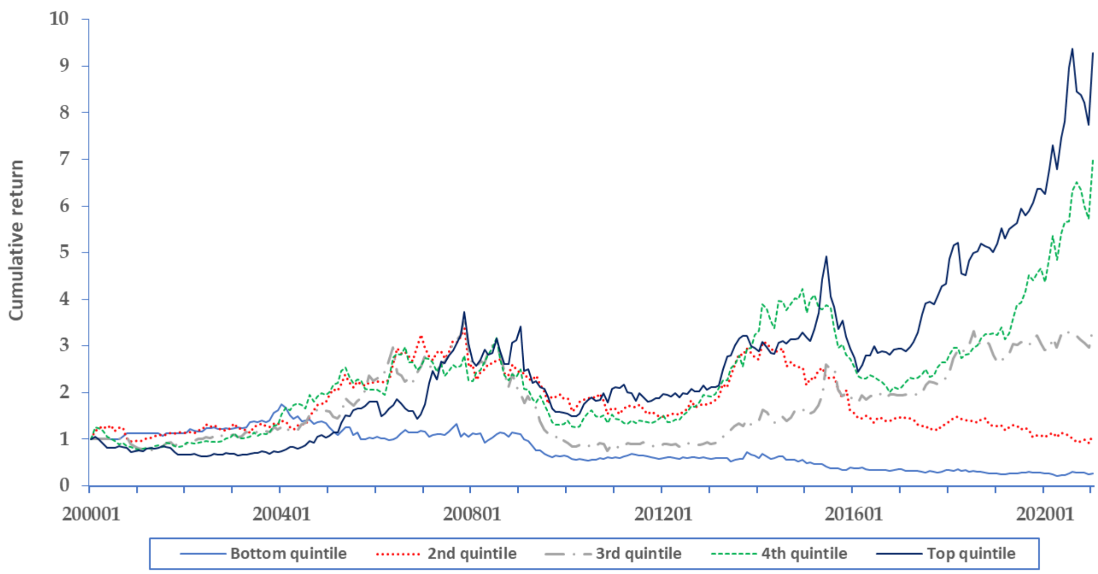
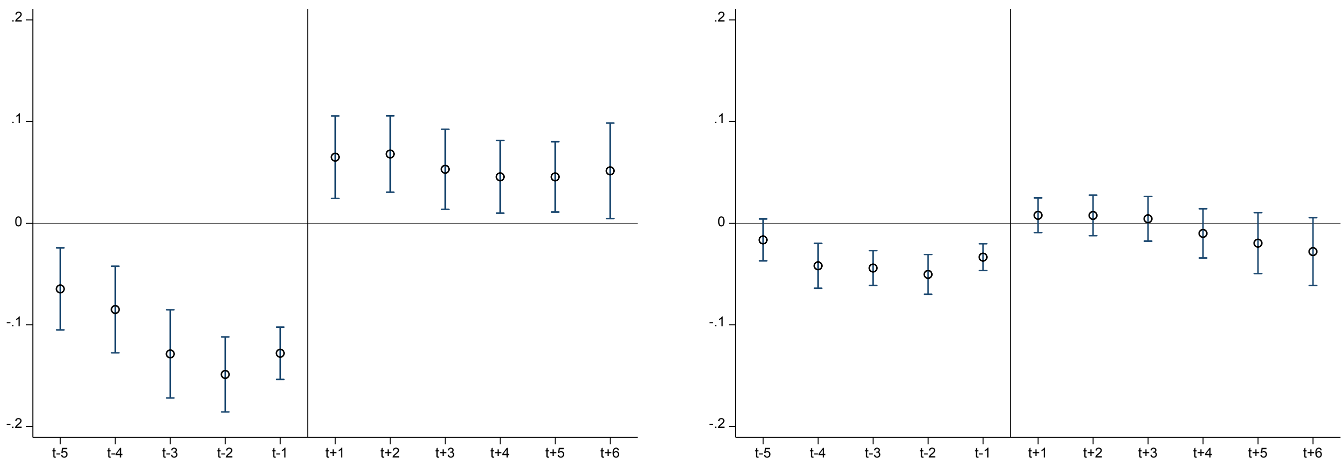


Figure 6: Investor participation in high-priced stocks around stock splits

This figure shows the time-series patterns for participation in high-priced stocks (Quintile 5) by small and large investors around stock split events. The figure also shows the results for the rest of the stocks. We estimate the equation

$$Participation\_propensity_{i,t} = \alpha + \sum_{k=-5}^{6} \beta_k 1(EventMonth_{i,t} = k) + \tau_t + \nu_i + \varepsilon_{i,t}.$$

The dependent variable is the natural logarithm of the number of investors who hold the corresponding stock in month t. The figure plots the coefficients for each month in event time, relative to the omitted category of month $t-6$. Observations are at the stock-month level, and the sample is limited to the six months before and after a split. The dots represent the point estimates for the β_k coefficients and the vertical lines represent 90% confidence intervals. The coefficient on β_0 is not shown because event month $k=0$ contains both pre-split and post-split days. The estimation also includes stock (ν_i) and year-month (τ_t) fixed effects. t-values are double-clustered by stock and year-month.



Small investors

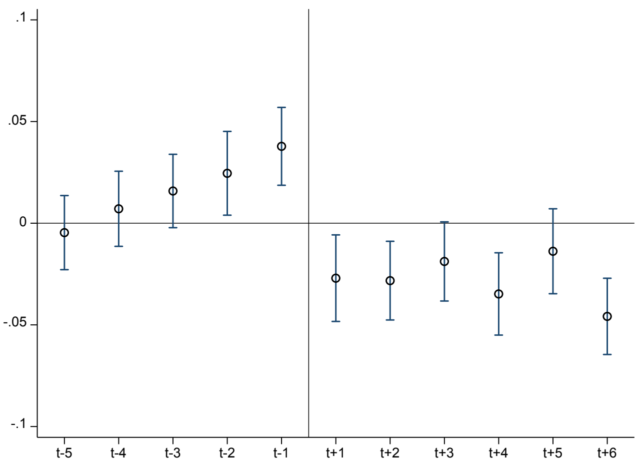
Large investors

Figure 7: Momentum around stock splits

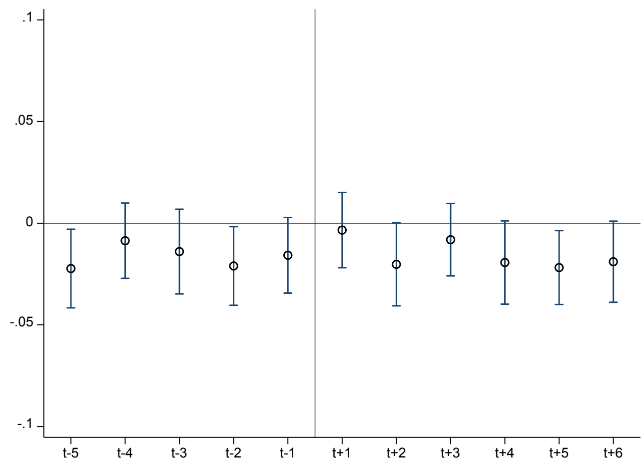
This figure shows the time-series patterns for stock-level momentum around stock split events for high-priced stocks and the rest of the stocks, separately. We estimate

$$I\_MOM_{i,t} = \alpha + \sum_{k=-5}^{6} \beta_k 1(EventMonth_{i,t} = k) + \tau_t + \nu_i + \varepsilon_{i,t}.$$

The dependent variable is a stock-level momentum indicator that equals one if the stock's past 12 months return is above (or below) the median and its current month return is also above (or below) the median. The figure plots the coefficients for each month in event time, relative to the omitted category of month *t-6*. Observations are at the stock-month level, and the sample is limited to the six months before and after a split. The dots represent the point estimates for the β_k coefficients and the vertical lines represent 90% confidence intervals. The coefficient on β_0 is not shown because event month $k = 0$ contains both pre-split and post-split days. The estimation also includes stock (ν_i) and year-month (τ_t) fixed effects. *t*-values are double-clustered by stock and year-month.



High-priced stocks



Non-high-priced stocks

Table 1: Summary statistics for investment characteristics of small and large investors

This table reports summary statistics of investment characteristics for small and large investors, respectively. We present percentile values for each row variable where "px" represents the x'th percentile. Panel A reports the stock portfolio characteristics of small investors (with average portfolio size below 200k yuan) and large investors (with average portfolio size above 500k yuan). The investor holdings sample period is from January 2016 to June 2020, and the sample period for trades is from January 2018 to June 2020. "Average stock price" is the time-series average month-end price of stocks. "Average value per stock held" is the average value per stock held per investor based on investors' monthly statements. "Price constraint" is the average value of stock holdings divided by 400. "Average # shares per stock" is the mean number of shares per stock per investor. "Average # stocks" is the average number of stocks held per month per investor. "Trade size" is the average dollar value of trades per investor. "Trade times per month" is the average number of trades per month per investor. "Holding period" is the average number of days to sale per investor. "Turnover" is the annualized monthly turnover. "Average price" is the average month-end price of stocks held per investor. "Average price rank" is the average price-based decile ranking of stocks held per investor. Panel B reports the participation propensity on decile stock groups sorted by price. "Propensity" is the time-series average of the proportions of small investors (or large investors) who hold at least one stock in each decile stock group. "Weight" is the time-series average of the portfolio weights of small investors (or large investors) on the relevant stock group. The last two columns of Panel B report the number and the *t*-value for the difference between the fifth and tenth decile groups. The "*Diff in diff*" row reports the difference-in-difference between small and large investors.

Table 1, contd.

Panel A. Stock portfolio characteristics								
	Mean	p1	p10	p25	p50	p75	p90	p99
Average stock price	20.8	3.9	6.0	8.6	14.0	24.7	40.2	115.8
Small investors (with average portfolio size below 200k yuan)								
Average value per stock held	22,461.7	666.7	3,347.5	6,887.4	14,456.2	28,880.5	51,768.9	120,275.9
Price constraint	56.2	1.7	8.4	17.2	36.1	72.2	129.4	300.7
Average # shares per stock	2,999.1	100.0	417.3	863.5	1,776.3	3,581.0	6,689.5	18,909.2
Average # stocks	3.4	1.0	1.1	1.7	2.6	4.1	6.3	13.8
Trade size	17,532.9	1,092.8	2,953.0	5,371.4	10,446.9	20,633.8	38,988.4	107,726.2
Trade times per month	13.6	1.4	2.3	3.5	6.5	14.0	30.1	110.8
Holding period (days)	57.6	1.7	5.1	11.7	30.5	75.1	147.4	349.7
Turnover	214.3	0.0	17.5	52.0	138.8	309.7	544.9	884.1
Average price	12.0	2.9	5.0	6.8	9.8	14.3	20.6	43.7
Average price rank	4.2	1.0	1.9	2.8	4.1	5.5	6.7	8.7
Large investors (with average portfolio size above 500k yuan)								
Average value per stock held	1,844,968.0	22,876.9	64,436.6	115,352.6	226,787.3	483,561.8	1,097,917.0	8,107,338.0
Price constraint	4,612.4	57.2	161.1	288.4	567.0	1,208.9	2,744.8	20,268.3
Average # shares per stock	177,018.3	2,003.0	5,887.6	11,085.2	23,029.2	52,457.8	121,364.8	810,280.4
Average # stocks	8.2	1.0	2.1	3.3	5.4	9.3	15.8	47.4
Trade size	128,294.0	5,442.2	15,724.5	30,467.1	67,445.2	148,357.5	288,172.5	886,470.4
Trade times per month	26.1	1.4	2.5	4.2	8.8	21.5	51.7	254.3
Holding period (days)	102.9	3.2	12.3	28.2	68.4	143.3	245.2	468.0
Turnover	146.7	0.0	8.8	30.0	85.2	202.0	380.9	752.0
Average price	18.4	4.5	7.6	10.0	13.6	19.3	28.6	115.2
Average price rank	5.2	1.7	3.2	4.1	5.1	6.3	7.3	9.1

Panel B. Participation propensity each stock price decile											
Deciles by price	G1	G2	G3	G4	G5	G6	G7	G8	G9	G10	Diff	*t*-value
Propensity_small (%)	40.2	31.6	28.7	25.0	21.3	19.4	17.3	14.6	12.8	9.9	-11.41***	(-26.58)
Propensity_large (%)	44.8	42.4	42.8	41.1	38.6	39.6	38.6	35.5	33.3	30.6	-8.01***	(-10.60)
Diff in diff											-3.40***	(-6.79)
Weight_small (%)	15.5	12.2	11.6	10.5	9.3	9.0	8.6	7.8	7.5	7.9	-1.41***	(-3.94)
Weight_large (%)	7.1	7.3	8.5	8.4	8.0	13.1	18.4	10.0	8.7	10.3	2.32***	(3.31)
Diff in diff											-3.73***	(-4.84)

Table 2: Trading halt events and investors' buying propensity for high-priced stocks

This table reports the impact of trading halt events on investors' propensity to buy high-priced stocks. Panels A and B summarize the regression estimates for small and large investors, respectively. The regressions include investor buy trades in a three-month window prior to and after each investor-halt event. The dependent variable, *Buy_high*, denotes the fraction of total dollar buying volume of stocks whose price is in the top quintile on a given buying day. *Post* is a variable that is equal to one if the day is within the window of the trading halt event and zero otherwise. *Treat* is an indicator variable for investors in the treatment group whose holding stocks experience a trading-halt event. Control investor groups are matched with treatment groups on their portfolio sizes and their buy propensity on high-priced stocks three months prior to the event month. If indicated, the regressions include investor and day fixed effects. Marginal effects are displayed to the right of the coefficient estimates. *t*-values (in parentheses) are double-clustered at investor and day levels. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable: *Buy_high*							
	Small investors				Large investors			
	(1)	marginal effect	(2)	marginal effect	(3)	marginal effect	(4)	marginal effect
Treat×Post	-0.052***	-15.7%	-0.041***	-12.3%	-0.021	-5.6%	-0.013	-3.5%
	(-2.74)		(-2.78)		(-1.40)		(-1.05)	
Treat	0.018				0.033*			
	(0.73)				(1.68)			
Post	-0.003				-0.023			
	(-0.17)				(-1.47)			
Constant	0.332***				0.373***			
	(20.53)				(24.18)			
FE	N		Y		N		Y	
Observations	34,922		34,922		63,703		63,701	
R-squared	0.001		0.377		0.002		0.408	

Table 3: Returns on momentum and short-term reversal strategies

This table reports the monthly returns of momentum strategies and short-term reversal strategies across price-based deciles. We independently sort stocks into deciles groups based on nominal prices and quintile groups based on cumulative returns over past 12 (1) month(s) for the momentum (reversal) strategies. The sample period is from 2000 to 2020. Within each price decile, the momentum or short-term reversal strategy is constructed by buying the winner portfolio (top quintile) and selling the loser portfolio (bottom quintile). "Mean" reports the raw returns of the portfolios, whereas "FF5" reports the alphas from the Fama-French five-factor model. "All" presents the momentum (or reversal) strategy among all stocks. Newey-West *t*-values are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Stock price	*MOM* portfolios		Reversal portfolios	
	Mean	FF5	Mean	FF5
All	0.212	0.049	-1.222***	-1.160***
	(0.82)	(0.21)	(-4.87)	(-4.83)
Low	0.072	-0.027	-1.950***	-1.922***
	(0.16)	(-0.07)	(-4.28)	(-4.47)
2	-0.246	-0.326	-0.987***	-1.047***
	(-0.83)	(-1.13)	(-2.81)	(-3.22)
3	-0.018	-0.113	-2.052***	-1.790***
	(-0.06)	(-0.41)	(-5.76)	(-5.77)
4	0.127	-0.168	-1.141***	-1.074***
	(0.39)	(-0.54)	(-3.94)	(-3.81)
5	0.207	0.087	-1.623***	-1.526***
	(0.66)	(0.32)	(-6.05)	(-5.68)
6	0.284	0.040	-1.226***	-1.272***
	(1.11)	(0.15)	(-5.21)	(-5.73)
7	0.454*	0.365	-1.207***	-1.164***
	(1.70)	(1.35)	(-4.37)	(-4.39)
8	0.814***	0.708**	-1.123***	-1.093***
	(2.75)	(2.49)	(-4.22)	(-4.14)
9	0.732**	0.621*	-0.695**	-0.582*
	(2.38)	(1.94)	(-2.39)	(-1.82)
High	1.662***	1.771***	-0.319	-0.318
	(4.00)	(4.12)	(-0.98)	(-0.90)
10-5	1.456***	1.690***	1.304***	1.208***
	(3.48)	(4.05)	(3.84)	(3.12)
10-1	1.591***	1.772***	1.631***	1.591***
	(2.60)	(2.86)	(3.34)	(2.95)

Table 4: Fama-MacBeth regressions

This table reports the Fama-MacBeth regression results of one-month ahead stock returns on momentum, a high price dummy, and their interaction:

$$R_{i,t+1} = \alpha_t + \beta_1 MOM_{i,t} + \beta_2 High\ price_{i,t} + \beta_3 High\ price_{i,t} * MOM_{i,t} + \gamma_i Control_{i,t} + \varepsilon_{i,t},$$

where $MOM_{i,t}$ denotes the returns of stock i from month $t-11$ to month t-1 and $High\ price_{i,t}$ indicates stocks with prices in the top quintile as of the end of month t. $STR\ (LTR)$ denotes short-term (long-term) reversals measured as the cumulative returns over the past one month (five years). Other interaction terms include size, 52-week high, information discreteness (*FIP*), and the aggregate holdings of the institutions defined in CSMAR (*Institution*). Momentum and all continuous variables in each month are standardized to have a zero mean and unit standard deviation each month. Control variables include book-to-market, gross profitability, size, asset growth, and the current month's return. The sample period is January 2000-December 2020. Newey-West t-values are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable: One-month ahead monthly returns							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MOM	0.035	-0.034	-0.032	-0.083	-0.038	-0.012	-0.047	-0.020
	(0.42)	(-0.42)	(-0.40)	(-1.06)	(-0.48)	(-0.17)	(-0.57)	(-0.25)
MOM ×*High price*		0.230***	0.204***	0.246***	0.167***	0.160**	0.221***	0.137**
		(3.57)	(3.25)	(3.86)	(2.70)	(2.25)	(3.60)	(2.24)
STR× *High price*			0.210***					
			(3.02)					
LTR× *High price*				-0.015				
				(-0.27)				
MOM ×*Size*					0.096***			
					(3.30)			
MOM ×*High52*						0.085**		
						(2.49)		
MOM × *FIP*							0.027	
							(0.98)	
MOM × *Institution*								0.112***
								(4.08)
High price		-0.134	-0.191	-0.138	-0.123	-0.126	-0.124	-0.153
		(-0.99)	(-1.43)	(-1.02)	(-0.91)	(-0.91)	(-0.92)	(-1.19)
Control Variables	Y	Y	Y	Y	Y	Y	Y	Y
R-squared	0.078	0.085	0.087	0.087	0.087	0.093	0.087	0.090
Average # of stocks	1,304	1,304	1,304	1,304	1,304	1,304	1,304	1,304
Number of months	252	252	252	252	252	252	252	252

Table 5: Fama-Macbeth regressions for high-priced stocks

This table reports the Fama-MacBeth regression results of one-month ahead stock returns on the momentum variable, explanatory variables, and their interactions, for high-priced stocks (the top quintile of market price):

$$R_{i,t+1} = \alpha_t + \beta_1 MOM_{i,t} + \beta_2 X_{i,t} + \beta_3 X_{i,t} * MOM_{i,t} + \gamma_i Control_{i,t} + \varepsilon_{i,t},$$

where $MOM_{i,t}$ denotes the cumulative returns of stock i from month $t-11$ to month t-1, and X denotes the explanatory variables in month t, namely, book-to-market, residual analyst coverage, analysts' revisions, turnover, 52-week high, information discreteness (*FIP*), and the aggregated holdings of the institutions defined in CSMAR, including funds, QFII, brokers, insurance companies, security funds, trusts, finance and non-finance companies, banks, and other miscellaneous categories. Momentum and all X variables in each month are standardized to have a zero mean and unit standard deviation. Control variables include book-to-market, gross profitability, size, asset growth, and the current month's return. The sample period is between January 2000 and December 2020. Newey-West t-values are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Without controls				With controls			
X-variable	β_1	β_2	β_3	R^2	β_1	β_2	β_3	R^2
	0.245**			0.027	0.189 **			0.099
	(2.63)				(2.04)			
Book-to-market	0.199**	0.083	-0.066	0.040	0.166	0.057	-0.032	0.107
	(1.96)	(0.87)	(-1.10)		(1.58)	(0.64)	(-0.55)	
Residual analyst coverage	0.217**	0.297***	0.019	0.041	0.160 *	0.251 ***	0.029	0.113
	(2.42)	(4.90)	(0.63)		(1.76)	(4.49)	(1.06)	
Analysts' revisions	0.228**	0.150**	0.004	0.035	0.168 *	0.173 ***	0.000	0.110
	(2.49)	(2.41)	(0.12)		(1.86)	(2.95)	(0.01)	
Turnover	0.264***	-0.419***	-0.078	0.063	0.236 **	-0.481 ***	-0.104 **	0.131
	(2.65)	(-4.61)	(-1.64)		(2.43)	(-5.53)	(-1.91)	
52-week high	0.178**	0.106	0.077	0.053	0.139	0.304 ***	0.062	0.121
	(1.99)	(0.90)	(1.53)		(1.58)	(2.62)	(1.31)	
FIP	0.264***	-0.031	-0.022	0.039	0.188 **	-0.054	-0.010	0.112
	(2.78)	(-0.50)	(-0.38)		(2.01)	(-0.88)	(-0.18)	
Return volatility	0.411***	-0.228**	-0.172 ***	0.065	0.387 ***	-0.141	-0.195 ***	0.129
	(3.94)	(-2.30)	(-3.94)		(3.95)	(-1.29)	(-4.14)	
Institutional holdings	0.139	0.147*	0.124 ***	0.050	0.023	0.003	0.159 ***	0.125
	(1.52)	(1.78)	(2.95)		(0.25)	(0.04)	(3.96)	

Table 6: Event study of investor participation around stock splits: China

This table considers an event study of investor participation around stock splits and summarizes the results for investor participation in high-priced stocks (Quintile 5) and the rest of the stocks (Quintiles 1 to 4), respectively. The participation propensity is the natural logarithm of the number of investors who hold the corresponding stock in the month-end statements. In columns (1)–(3), the dependent variable is the participation propensity of small investors. In columns (4)–(6), the dependent variable is the participation propensity of large investors. In particular, the regressions estimate:

$$Participation\_propensity_{i,t} = \beta * After_{i,t} + \tau_t + \nu_i + \varepsilon_{i,t}.$$

After is an indicator variable, which is unity in the six months following a split and zero in the six months preceding a split. Columns (3) and (6) include the interaction terms between *After* and *Split ratio*, where the latter is the ratio of shares outstanding after the split to that before the split, minus one. The sample period is from January 2016 to June 2020. If indicated, the regressions include stock and year-month fixed effects. Marginal effects are displayed to the right of the coefficient estimates. t-values (in parentheses) are double-clustered at the stock and year-month levels. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 6, contd.

Panel A. High-priced stocks

	Participation probability of small investors					Participation probability of large investors				
	(1)	marginal effect	(2)	marginal effect	(3)	(4)	marginal effect	(5)	marginal effect	(6)
After	0.229***	25.7%	0.113***	12.0%	0.112***	0.102***	10.7%	0.012	1.2%	0.012
	(5.67)		(5.11)		(6.76)	(2.93)		(0.95)		(0.93)
After×Split ratio					0.298***					0.072***
					(8.48)					(3.88)
Constant	2.459***					3.551***				
	(62.49)					(103.23)				
FE	N		Y		Y	N		Y		Y
Observations	10,582		10,582		10,582	10,582		10,582		10,582
R-squared	0.020		0.838		0.846	0.005		0.922		0.923

Panel B. Non-high-priced stocks

	Participation probability of small investors					Participation probability of large investors				
	(1)	marginal effect	(2)	marginal effect	(3)	(4)	marginal effect	(5)	marginal effect	(6)
After	0.170***	18.5%	0.104***	11.0%	0.087***	0.102***	10.7%	0.045***	4.6%	0.038***
	(4.32)		(5.06)		(5.11)	(3.04)		(3.55)		(3.10)
After×Split ratio					0.189***					0.085***
					(6.60)					(4.57)
Constant	3.195***					3.936***				
	(79.14)					(119.48)				
FE	N		Y		Y	N		Y		Y
Observations	11,689		11,689		11,689	11,689		11,689		11,689
R-squared	0.012		0.913		0.916	0.005		0.957		0.957

Table 7: Event study of momentum around stock splits: China

This table reports results from an event study of stock-level momentum around stock splits. The regressions estimate:

$$I\_MOM_{i,t} = \beta * After_{i,t} + \tau_t + \nu_i + \varepsilon_{i,t}.$$

The dependent variable is a stock-level momentum indicator which equals one if the stock's past 12-month return is above (or below) the cross-sectional median and its current month's return is also above (or below) the corresponding median. The sample period is from January 2000 to December 2020. *After* is an indicator variable which is unity in the six months following a split, and zero in the six months preceding a split. Column (3) adds the interaction terms between *After* and *Split* ratio, where the latter is the ratio of shares outstanding after the split to that before the split, minus one. If indicated, the regressions include stock and year-month fixed effects. Marginal effects are displayed to the right of the coefficient estimates. *t*-values (in parentheses) are double-clustered at stock and year-month level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A. High-priced stocks					
	Dependent Variable: stock-level momentum				
	(1)	marginal effect	(2)	marginal effect	(3)
After	-0.034***	-6.3%	-0.036***	-6.7%	-0.036***
	(-4.06)		(-4.70)		(-4.69)
After×Split ratio					-0.038***
					(-3.20)
Constant	0.539***				
	(68.86)				
FE	N		Y		Y
Observations	44,025		44,025		44,025
R-squared	0.001		0.086		0.086
Panel B. Non-high-priced stocks					
	Dependent Variable: stock-level momentum				
	(1)	marginal effect	(2)	marginal effect	(3)
After	0.001	0.2%	-0.005	-1.0%	-0.005
	(0.14)		(-0.77)		(-0.73)
After×Split ratio					-0.032**
					(-2.49)
Constant	0.500***				
	(102.63)				
FE	N		Y		Y
Observations	47,013		47,013		47,013
R-squared	0.000		0.055		0.055

Appendix A: Extra Tables

Table A.1: Summary statistics for investment characteristics of small and large investors: A different cutoff

This table reports summary statistics of investment characteristics for small and large investors, respectively. We present percentile values for each row variable where "px" represents the x'th percentile. Panel A reports the stock portfolio characteristics of small investors (with average portfolio size below 100k yuan) and large investors (with average portfolio size above 1M yuan). The investor holdings sample period is from January 2016 to June 2020, and the sample period for trades is from January 2018 to June 2020."Average value per stock held" is the average value per stock held per investor based on investors' monthly statements. "Price constraint" is the average value of stock holdings divided by 400. "Average # shares per stock" is the mean number of shares per stock per investor. "Average # stocks" is the average number of stocks held per month per investor. "Trade size" is the average dollar value of trades per investor. "Trade times per month" is the average number of trades per month per investor. "Holding period" is the average number of days to sale per investor. "Turnover" is the annualized monthly turnover. "Average price" is the average month-end price of stocks held per investor. "Average price rank" is the average price-based decile ranking of stocks held per investor. Panel B reports the participation propensity on decile stock groups sorted by price. "Propensity" is the time-series average of the proportions of small investors (or large investors) who hold at least one stock in each decile stock group**.** "Weight" is the time-series average of the portfolio weights of small investors (or large investors) on the relevant stock group. The last two columns of Panel B report the number and the *t*-value for the difference between the fifth and tenth decile groups. The "*Diff in diff*" row reports the difference-in-difference between small and large investors.

Table A.1, contd.

Panel A.1.1 Stock portfolio characteristics								
	Mean	p1	p10	p25	p50	p75	p90	p99
			Small investors (with average portfolio size below 100k yuan)					
Average value per stock held	15,330.1	562.4	2,853.9	5,660.5	11,107.5	20,126.5	33,483.8	69,112.1
Price constraint	38.3	1.4	7.1	14.2	27.8	50.3	83.7	172.8
Average # shares per stock	2,145.2	100.0	357.5	708.0	1,397.5	2,617.6	4,670.4	12,384.2
Average # stocks	3.0	1.0	1.0	1.6	2.4	3.7	5.5	11.5
Trade size	12,725.2	995.8	2,587.3	4,525.8	8,384.4	15,474.5	26,761.5	68,099.6
Trade times per month	12.2	1.4	2.3	3.4	6.1	12.7	26.8	92.3
Holding period (days)	55.0	1.6	4.9	11.0	28.5	70.9	140.2	335.1
Turnover	219.5	0.0	18.0	53.3	143.1	319.1	556.2	892.1
Average price	11.8	3.6	5.4	7.0	9.8	14.1	20.1	41.0
Average price rank	4.1	1.0	1.7	2.7	3.9	5.3	6.6	8.6
			Large investors (with average portfolio size above 1M yuan)					
Average value per stock held	3,455,597.0	36,221.8	111,961.5	207,824.1	413,965.4	878,419.2	1,983,004.0	15,400,000
Price constraint	8,639.0	90.6	279.9	519.6	1,034.9	2,196.0	4,957.5	38,500.0
Average # shares per stock	327,011.5	3,078.4	9,911.1	19,060.6	40,444.0	91,433.7	210,718.1	1,628,533.0
Average # stocks	8.9	1.0	2.2	3.4	5.7	10.0	17.5	54.0
Trade size	181,093.4	7,022.9	21,589.5	44,476.3	101,409.0	215,454.7	400,973.0	1,166,754.0
Trade times per month	32.1	1.4	2.6	4.4	9.6	24.3	59.3	332.2
Holding period (days)	110.3	3.3	13.6	31.2	75.3	153.9	261.2	488.6
Turnover	137.2	0.0	6.8	26.5	78.3	190.0	356.1	714.3
Average price	20.1	5.4	8.5	10.8	14.5	20.3	30.4	138.1
Average price rank	5.3	1.8	3.3	4.2	5.2	6.3	7.4	9.1

Panel A.1.2 Participation propensity each stock price decile											
Deciles by price	G1	G2	G3	G4	G5	G6	G7	G8	G9	G10	Diff	*t*-value
Propensity_small (%)	40.2	30.5	27.2	23.2	19.4	17.3	15.1	12.4	10.6	7.8	-11.63***	(-30.52)
Propensity_large (%)	44.4	42.8	43.7	42.5	40.0	41.6	40.8	37.7	35.6	32.9	-7.08***	(-9.56)
Diff in diff											-4.55***	(-8.36)
Weight_small (%)	17.4	13.0	12.1	10.8	9.4	8.8	8.1	7.2	6.7	6.5	-2.93***	(-10.14)
Weight_large (%)	6.5	7.0	8.3	8.2	7.9	13.5	19.4	10.2	8.7	10.3	2.44***	(3.33)
Diff in diff											-5.37***	(-7.00)

Table A.2: Returns on momentum: Sequential sort

This table reports the monthly returns of momentum strategies across price-based deciles. The sample period is from 2000 to 2020. We sequentially sort stocks into deciles based on nominal prices and quintiles based on cumulative returns over the past 12 months. Within each price decile, the momentum strategy is constructed by buying the winner portfolio (top quintile) and selling the loser portfolio (bottom quintle). "Mean" reports the average raw returns of the portfolios, whereas "FF5" reports the alphas from the Fama-French five-factor model. "All" presents profits from applying the momentum strategy to all stocks, which is copied from Table 3. Newey-West *t*-values are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Stock price	Mean	FF5
All	0.212	0.049
	(0.82)	(0.21)
Low	0.313	0.120
	(1.27)	(0.51)
2	-0.079	-0.149
	(-0.34)	(-0.69)
3	0.172	0.047
	(0.77)	(0.21)
4	0.151	-0.032
	(0.60)	(-0.12)
5	0.236	0.181
	(0.79)	(0.69)
6	0.231	0.010
	(0.88)	(0.04)
7	0.409	0.297
	(1.58)	(1.12)
8	0.570**	0.507*
	(2.10)	(1.90)
9	0.688**	0.605**
	(2.41)	(2.00)
High	1.435***	1.532***
	(3.71)	(3.63)
10-5	1.199***	1.351***
	(3.10)	(3.24)
10-1	1.123***	1.412***
	(2.73)	(3.11)

Table A.3: Reversal portfolios across illiquidity and price quintiles

This table reports the average returns of reversal strategies across illiquidity and price quintiles. At the end of month *t*, all stocks are sequentially sorted into quintiles based on Amihud illiquidity, stock price, and return of month *t*. Within each illiquidity-price interaction, a reversal strategy is constructed by buying the winner portfolio and selling the loser portfolio. Newey-West *t*-values are reported in parentheses. ***, **, * denote significance at 1%, 5%, and 10% levels, respectively.

	Amihud illiquidity				
Price	Low	2	3	4	High
Low	-0.260	-1.330***	-1.743***	-2.424***	-1.501**
	(-0.50)	(-2.68)	(-3.85)	(-5.30)	(-2.41)
2	-1.134**	-0.879**	-2.011***	-2.644***	-2.071***
	(-2.45)	(-2.46)	(-5.93)	(-6.58)	(-4.83)
3	-0.096	-0.962**	-1.678***	-1.948***	-2.885***
	(-0.24)	(-2.53)	(-3.88)	(-4.94)	(-6.61)
4	-0.981**	-1.017***	-1.633***	-1.530***	-1.721***
	(-2.48)	(-2.94)	(-4.07)	(-3.68)	(-4.60)
High	-0.276	-1.107***	-0.710*	-0.760*	-0.429
	(-0.65)	(-2.74)	(-1.79)	(-1.72)	(-0.92)

Table A.4: Fama-MacBeth regressions for U.S. stocks

This table reports the Fama-MacBeth regression results of one-month ahead stock returns on the momentum variable (*MOM*) and its interaction with a *Lottery* stock dummy, where Lottery stocks are defined, in turn, as in Kumar (2009) (based on a 5x5x5 sort on market capitalization, as well as past-six-months' skewness and volatility), and in Bali, Cakici, and Whitelaw (2011) (where the sorts are instead based on market capitalization and the maximum return in the current month). Control variables include book-to-market, gross profitability, size, asset growth, the current month's return. The sample period is between January 1976 and December 2020. Newey-West *t*-values are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: The Kumar (2009) method				
	Dependent variable: one-month ahead monthly return			
	Without controls		With controls	
MOM	0.209**	0.249***	0.251***	0.293***
	(2.60)	(3.17)	(3.24)	(3.86)
Lottery		0.398		0.337
		(1.43)		(1.29)
*Lottery*MOM*		-0.468***		-0.582***
		(-4.39)		(-5.43)
R^2	0.010	0.014	0.025	0.029

Panel B: The Bali, Cakici, and Whitelaw (2011) method				
	Dependent variable: one-month ahead monthly return			
	Without controls		With controls	
MOM	0.204**	0.307***	0.244***	0.347***
	(2.52)	(3.90)	(3.12)	(4.51)
Lottery		0.453*		0.492**
		(1.88)		(2.14)
*Lottery*MOM*		-0.641***		-0.704***
		(-6.41)		(-6.88)
R^2	0.009	0.016	0.024	0.030

Appendix B: An Analytical Setting

We propose a simple setting with institutional and retail investors to motivate our empirical tests in Section 4. The setting is a modification of the model in Grinblatt and Han (2005). We assume the single risky stock is in fixed supply, normalized to one unit. There are two investor types: institutions and retail investors. The retail investors constitute a fixed fraction μ of all investors. Retail investors' demand has a component that reacts naïvely to past short-horizon returns.[53] The assumed demand functions for each investor type are:

Institutional demand: $$D_t^{inst} = 1 + b_t\,(F_t - P_t), \tag{B.1}$$

Retail demand: $$D_t^{retail} = 1 + b_t\,[(F_t - P_t) + \lambda\,(P_t - P_{t-1})], \tag{B.2}$$

where P_t is the price of the stock; F_t is the rational date-t updated belief about the future payoff; b_t represents the slope of the belief-dependent component of the demand function for the stock; and λ is a positive constant that measures the degree to which retail demand is naïvely based on past price changes.[54] Each unit of the time index t is assumed to span a short horizon of a month or less.

Institutions are quasirational relative to retail traders in that they do not have naïve demands that are not justified by fundamental news arrival. However, this does not necessarily mean that their subjective belief is fully rational, as we will see. By aggregating investors' demand functions and clearing the market, we derive the market price in Eq. (3) and price changes in Eq. (4).

$$P_t = (1 + \omega)F_t - \omega P_{t-1}, \text{ where } \omega \equiv \frac{\mu\lambda}{1-\mu\lambda} \text{ and } \mu\lambda < 1. \tag{B.3}$$

[53] This assumption is motivated by the findings in Jones et al. (2022) that retail investors chase returns over daily horizons.

[54] It is possible to have the institutional demand also depend on past price changes. All that is needed for our results is that the slope of this dependence be larger for retail investors.

$$P_{t+1} - P_t = (1 + \omega)(F_{t+1} - F_t) - \omega(P_t - P_{t-1}). \quad \text{(B.4)}$$

Thus, price changes are determined by fundamental belief shifts, $F_{t+1} - F_t$, and past price changes, $P_t - P_{t-1}$. The inequality $\mu\lambda < 1$ stipulates that the trend-chasing component of retail investors' demand is not so strong as to make the price explode. The second term of Eq. (B.4) indicates a partial reversal of the previous price change as the effect of naïve trend-chasing on prices reverses.

To show implications for how retail trading affects stock momentum, we perform simulations that capture the dynamics of asset prices. Without loss of generality, the expected price change conditional on positive news can be expressed as

$$\mathrm{E}[(P_{t+1} - P_t)|\text{pos.news}] =$$

$$(1 + \omega)\mathrm{E}[(F_{t+1} - F_t)|\text{pos. news}] - \omega\mathrm{E}[(P_t - P_{t-1})|\text{pos. news}]. \quad \text{(B.5)}$$

We first consider a simple case in which there is no retail trading ($\omega = 0$). In this case, equation (B.5) reduces to

$$\mathrm{E}\big[(P_{t+1} - P_{t)}\big| \text{ pos. news}] = \mathrm{E}[(F_{t+1} - F_t)| \text{ pos. news}], \quad \text{(B.6)}$$

wherein price changes are fully determined by changes in beliefs about fundamentals.

Next, we look at another benchmark case in which investor beliefs are rational (and follow martingales) to study the impact of retail trading. In this case, Eq. (B.5) becomes

$$\mathrm{E}\big[(P_{t+1} - P_{t)}\big| \text{ pos. news}] = -\omega\mathrm{E}[(P_t - P_{t-1})| \text{ pos. news}]. \quad \text{(B.7)}$$

Figure B.1, Panel B.1.1 reports simulations of the price dynamics for different values of ω.[55] We find short-term reversals when retail investors are prevalent (high ω). However, there is no momentum because there is no drift in beliefs about fundamentals.

[55] The initial condition for the simulation is $P_0 = 0$. From equation (B.3), this condition thus assumes that there are no retail investors prior to time 0 and that the fundamental belief at time zero $F_0 = 0$. Equation

[Insert Figure B.1]

Last, we consider the case in which biased belief updating interacts with retail investors' presence. We assume a positive drift, θ, in fundamental beliefs, conditional on the initial positive news. Thus, $\mathrm{E}[(F_{t+1} - F_t)|\text{ pos. news}] = \theta$. Equation (B.5) then becomes

$$\mathrm{E}\big[(P_{t+1} - P_{t)})\big|\text{ pos. news}] = (1 + \omega)\theta - \omega\mathrm{E}[(P_t - P_{t-1})|\text{ pos. news}]. \quad \text{(B.8)}$$

Panel B.1.2 of Figure B.1 shows the resulting price dynamics for high and low values of ω. One can detect momentum when retail trading is low but momentum is hard to discern when the extent of retail trading is high. The latter happens because naïve trading by retail investors (and the concomitant price reversal) counteracts drifts in fundamental beliefs.[56]

We summarize our predictions regarding the relationship between the fraction of retail investors and return predictability as follows.

1. *When fundamental beliefs follow a martingale, there is no momentum. An increase (decrease) in the fraction of retail investors strengthens (weakens) short-term reversals.*
2. *Under persistent fundamental belief drift: momentum is strong (weak) when the fraction of retail traders is low (high). An increase (decrease) in the fraction of retail traders dampens (strengthens) momentum and strengthens (weakens) short-term reversals.*

The above predictions motivate our empirical tests in Section 4.

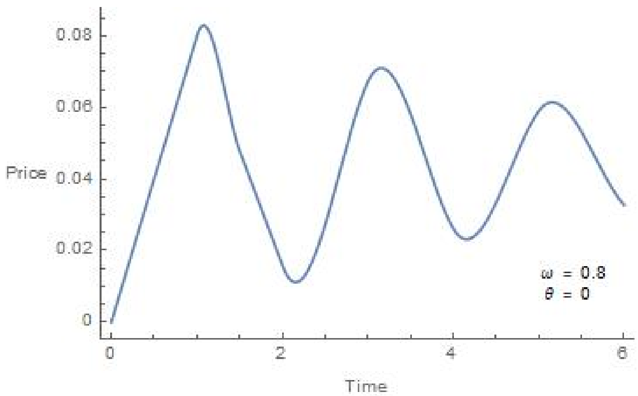
(B.7) then presents a way to compute a dynamic path for *E[P(t)]*, which is plotted in Panel B.1.1 of Figure B.1. A similar procedure applies to Panel B.1.2, which is based on equation (B.8) to follow.

[56] Similar results obtain if retail investors submit completely random demands that have to be accommodated by risk averse market makers. In this case, the inventory premia required to accommodate noise trades result in reversals, while underreaction to information causes momentum (see Chui, Subrahmanyam, and Titman 2022). Also, if retail investors chase long-term trends, it is possible to obtain long-term reversals (Hong and Stein 1999). Such long-term phenomena are beyond the scope of our paper. Our assumption that retail investors conduct short-horizon trend-chasing trades is consistent with the empirical finding in Jones et al. (2022).

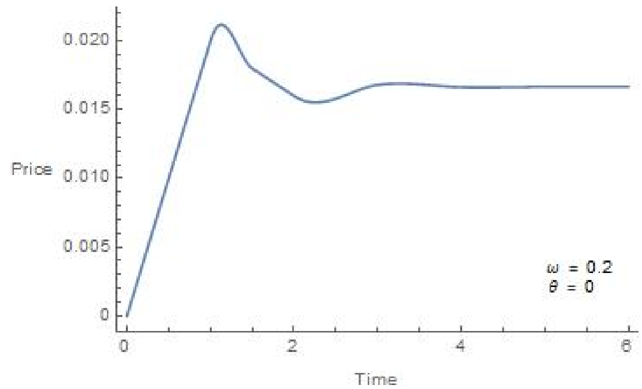
Figure B.1 Price dynamics with retail and institutional trading

This figure shows the results of simulating price dynamics based on Eq. (B.5). Panel B..1.1 shows the case in which there is no fundamental belief drift, and Panel B.1.2 the case with belief drift ($\theta = 0.005$). The variable ω denotes the extent of retail trading in the market.

Panel B.1.1: No fundamental belief drift

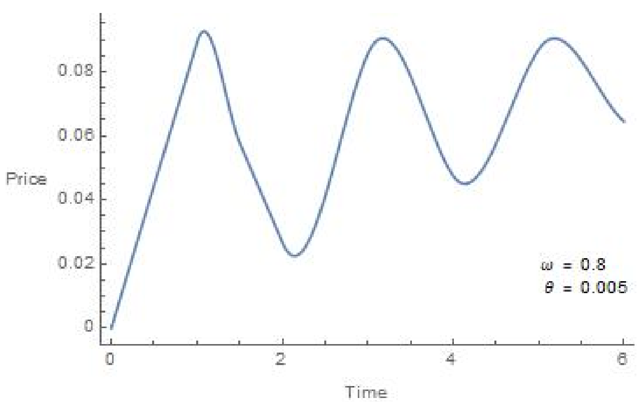


High levels of retail trading

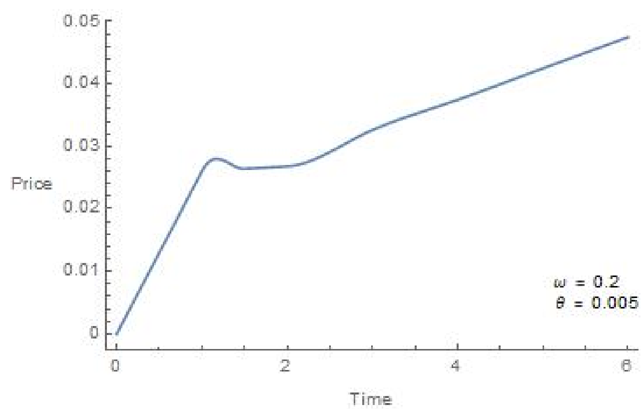


Low levels of retail trading

Panel B.1.2: Positive fundamental belief drift



High levels of retail trading



Low levels of retail trading