Daily Momentum and New Investors in Emerging Stock Markets*

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Abstract

Despite the dominance of retail investors, the Chinese stock market lacks price momentum in weekly and monthly returns. However, this study uncovers significant daily price momentum, driven by the attention and trading behaviors of new investors. This phenomenon, rooted in emerging markets' unique investor dynamics, highlights the outsized role of inexperienced investors. Our analysis extends globally, revealing daily price momentum in several emerging markets, while it remains scarce in developed ones. This divergence underscores the contrasting forces shaping market behavior in emerging versus developed stock markets, offering fresh insights into the role of investor composition in influencing market efficiency.

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The interplay between price momentum and reversal effects in stock markets has long fascinated academics and practitioners alike. In the U.S., the coexistence of medium-term price momentum—spanning one to twelve months (e.g., Jegadeesh and Titman (1993))—and long-term price reversals, extending over two to five years (e.g., De Bondt and Thaler (1985)), is a cornerstone of behavioral finance. Seminal works, such as Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998), and Hong and Stein (1999), have argued that these phenomena stem from cognitive biases influencing retail investors. Yet, such theories face a formidable challenge when applied to China's stock market, a context that seems, at first glance, tailor-made for testing these ideas.

China, with the second-largest stock market in the world and over 4,700 listed firms, is dominated by retail investors—a group often thought most susceptible to behavioral biases.[1] However, medium-term price momentum is conspicuously absent, e.g., Chui, Titman, and Wei (2010) and Du, Huang, Liu, Shi, Subrahmanyam, and Zhang (2022). Studies (e.g., Liu, Stambaugh, and Yuan (2019)) instead reveal a striking pattern of reversals: past returns over horizons ranging from one month to five years consistently predict future underperformance, overturning expectations of momentum effects. This puzzling divergence invites deeper scrutiny into the underlying mechanics of price dynamics in China's markets.

Our inquiry into this anomaly uncovers a nuanced picture. While medium-term momentum is absent, we observe a pronounced daily price momentum: stocks that perform well today often continue their rise tomorrow, only to reverse within a week. This phenomenon persists across both equally and value-weighted portfolios and is unaffected by the exclusion of stocks hitting daily price limits. Intriguingly, the effect intensifies during bullish markets but weakens in bearish conditions, underscoring its asymmetrical nature.

Why does daily momentum exist, but not its medium-term counterpart? The answer lies in the behaviors of different investor groups. Leveraging granular transaction data from the Shenzhen Stock Exchange (SZSE) spanning 2005 to 2019, we analyze trading patterns

[1]See Song and Xiong (2018), Hu, Pan, and Wang (2021), and Allen, Qian, Shan, and Zhu (2020) for reviews of the Chinese stock market.

across five categories of investors, revealing stark contrasts in their contributions to market dynamics.

Notably, Chinese stock exchanges offer a unique advantage: they can track an individual's trading activities across multiple brokerage firms using a unique national ID, a feature rarely available in other global exchanges. This capability enables a comprehensive view of individual and group trading behaviors, yielding insights into the forces shaping short-term momentum in China's markets.

One of the most intriguing drivers of China's stock market dynamics is the "new investor." Since the market's inception in the early 1990s, waves of inexperienced participants have regularly entered the fray, lured by the promise of rapid gains. These novice traders, often ill-equipped to navigate the complexities of market forces, display a pronounced reactivity to daily price movements—a pattern of behavior not unique to China but emblematic of emerging markets more broadly. Their behavior highlights the critical importance of examining the role of new investors in shaping short-term market outcomes. For this study, we define "new investors" as those who opened accounts within the preceding three months, have balances below three million yuan, and executed at least one trade during this period.

Beyond these newcomers, our analysis segments retail investors into two additional categories: "general retail investors," with account balances under three million yuan and account age exceeding three months, and "large retail investors," with balances exceeding this threshold above three million yuan. Institutional investors are divided into mutual funds and other entities. By meticulously tracking the net buying activity of these five groups across all SZSE-listed stocks on a daily basis, we construct a granular view of the forces at play.

The contrast between these groups is striking. New and general retail investors exhibit remarkably high daily turnover rates of 18.12% and 8.03%, respectively. Yet their frenetic trading activity is marred by poor stock selection: their monthly net buying is negatively correlated with subsequent returns, underscoring their role as noise traders in the market.

New investors, in particular, represent an intensified archetype of noise trading, distinguished only by the arbitrary three-month experience threshold.

In contrast, large retail investors, mutual funds, and other institutions display lower turnover rates and far superior stock selection skills. Their monthly net buying positively predicts subsequent returns, marking them as stabilizing forces amid the market's turbulence.

To pinpoint the key driver of daily price momentum, we probe deeper into the relationship between investor behavior and stock returns. Specifically, we examine whether a stock's current-day return correlates with the interaction of its prior-day return and a specific group's net buying activity. This approach provides a direct link between observed price momentum and investor trading patterns.

The results are revealing. New investors exhibit a pronounced tendency to chase prior-day returns, with their daily net buying closely aligned with stocks' performance on the previous day. This behavior amplifies daily momentum, as their buying drives stocks higher in the short term. However, this same pattern predicts reversals in the weeks that follow, underscoring their destabilizing influence.

Conversely, large retail investors act as a counterbalance. Their net buying is negatively correlated with stocks' prior-day returns, suggesting a contrarian approach. This behavior dampens momentum in the short term and is positively associated with stock returns in subsequent weeks, highlighting their stabilizing role.

Mutual funds present a more complex narrative. While their daily net buying appears to align with momentum trading, a deeper analysis reveals a subtler role. The interaction between prior-day returns and their buying activity negatively correlates with same-day returns but positively predicts returns over the following week and month. This nuanced behavior positions mutual funds as a tempering force, counteracting the excesses of short-term momentum while supporting longer-term stability.

Taken together, these findings illuminate the dynamics of China's daily price momentum. New and general retail investors are the primary contributors to short-term momentum and subsequent reversals. In contrast, large investors, mutual funds, and other institutions act as counterweights, mitigating volatility and restoring balance. Among these groups, the outsized influence of new investors is particularly pronounced, reinforcing their central role in shaping the market's distinctive price patterns.

The phenomenon of daily price momentum is far from unique to China's stock market. In a comparative analysis of global markets, including 21 emerging and 21 developed economies, we found compelling evidence of value-weighted daily price momentum in 14 emerging markets—a striking contrast to only three developed markets displaying similar patterns. Even more intriguing, many of these emerging markets exhibit an asymmetric response, with momentum effects far stronger during bullish periods than bearish ones, a feature reminiscent of the trend observed in China.

The role of new investors looms large in these markets. While their presence is clearly felt across emerging economies, the lack of granular, account-level data outside China limits a direct link between their trading behaviors and the daily momentum observed. Nonetheless, the prevalence of this effect in so many emerging markets strongly suggests a connection. It is likely that the intensified trading activity of new, inexperienced investors during bullish phases amplifies the momentum effects, reinforcing the asymmetrical patterns.

These international observations thus suggest a global pattern: the phenomenon of daily momentum is not merely a regional anomaly but a hallmark of emerging markets, underscoring the profound influence that new investors wield in shaping price dynamics across the world's developing economies.

This paper contributes to the long-standing literature on stock price momentum, exemplified by seminal works such as Jegadeesh and Titman (1993). While medium-term momentum—spanning 3 to 12 months—is a well-documented phenomenon across many global markets (Rouwenhorst (1998) and Griffin, Ji, and Martin (2003)), the Chinese stock market stands out as a notable exception. As highlighted by Chui et al. (2010) and Du et al. (2022), medium-term price momentum remains conspicuously absent in China. In this study, we not only confirm this absence but also uncover a previously undocumented and significant phenomenon: the presence of daily price momentum. By systematically analyzing the roles of different investor groups, we attribute this unique daily momentum to the trading behaviors of new investors, offering critical insights into the dynamics of the world's second-largest stock market.

Our findings also build upon the extensive literature on retail investors, reviewed comprehensively by Barber and Odean (2013). Much of the prior work on emerging markets has focused on China and India, with key contributions in the Indian context from Balasubramaniam, Campbell, Ramadorai, and Ranish (2023), Anagol, Balasubramaniam, and Ramadorai (2021), and Campbell, Ramadorai, and Ranish (2019). For China, important studies include Chen, Gao, He, Jiang, and Xiong (2019), Jones, Shi, Zhang, and Zhang (2020), An, Lou, and Shi (2022), Liu, Peng, Xiong, and Xiong (2022), Liao, Peng, and Zhu (2022), and Chen, Liang, and Shi (2022). A recurring theme across these works is the heterogeneity in trading behavior and performance among Chinese retail investors, often stratified by account balances. However, these studies have largely overlooked the critical role of new investors. In contrast, we systematically compare the contributions of new and other investor groups to daily price momentum—a phenomenon not only novel to the Chinese market but also evident across other emerging markets, further emphasizing the broader relevance of our findings.

Our study also intersects with the literature on investment experience. Greenwood and Nagel (2009) investigate how inexperienced versus experienced fund managers behaved during the tech bubble, using manager age as a proxy for experience. They find that younger managers were prone to trend-chasing and underperformed in tech stock investments. Similarly, Nicolosi, Peng, and Zhu (2009) and Seru, Shumway, and Stoffman (2010) explore how retail investors learn from trading experience. In our analysis, we identify new investors as those without prior stock trading experience, based on their brokerage account history, and examine the pricing implications of this inexperience, a dimension largely unexplored in prior work.

Moreover, this paper makes a substantive contribution to the literature on noise trading. Noise traders, as defined by (Kyle (1985) and Black (1986)), respond to market noise rather than fundamental information. This concept has become central to modern finance, underpinning numerous models of market dynamics (e.g.,De Long, Shleifer, Summers, and Waldmann (1990a,b), Campbell and Kyle (1993), and Stambaugh (2014), among many others). Empirical studies often characterize retail investors as noise traders, focusing on their role in creating mispricing (e.g., Lee, Shleifer, and Thaler (1991), Neal and Wheatley (1998), Nagel (2005), Kumar and Lee (2006), Barber, Odean, and Zhu (2008), and Da, Engelberg, and Gao (2015)). We extend this literature by highlighting the significant heterogeneity among retail investors, showing that the trading activity of new investors is a more reliable indicator of noise trading.

The structure of our paper is organized as follows: Section I examines the presence of price momentum across different time horizons in the Chinese stock market. Section II explores the relationship between the observed daily price momentum and the trading behaviors of new investors as well as other investor groups. Section III broadens the analysis to investigate the daily momentum phenomenon in major emerging and developed markets worldwide. Section IV concludes the paper.

I. Price Momentum

In this section, we investigate potential momentum effects across various time horizons in the Chinese stock market. Using the China Stock Market and Accounting Research (CSMAR) database, we collect daily, weekly, and monthly stock return data. Our sample spans the period from 2005 to 2019 and includes stocks listed on both the Shanghai Stock Exchange (SHSE) and the Shenzhen Stock Exchange (SZSE), China's two primary stock exchanges.

Table I presents summary statistics for the stocks in our sample, covering each year from 2005 to 2019. The sample includes all stocks listed on SHSE and SZSE. As the Chinese stock market expanded, the number of listed stocks grew significantly, from 1,466 in 2005 (830 on SHSE and 536 on SZSE) to 3,697 in 2019 (1,496 on SHSE and 2,201 on SZSE). This substantial number of stocks makes our analysis of momentum effects feasible. Notably, the SZSE alone provides a sufficiently large sample for subsequent analysis, which uses account-level data from SZSE to examine trading behavior among different investor groups.

Many listed firms in China are state-owned, and their share structures historically included non-tradable shares. These consist of state shares directly owned by the government or state-owned holding companies and legal-person shares held by domestic institutions, such as other SOEs, investment entities, or legally registered organizations. These non-tradable shares allowed the state to retain ownership and control of key firms but often created governance challenges, as controlling shareholders prioritized state interests over profitability. To address these inefficiencies, China launched a 2005 reform to convert most non-tradable shares into tradable ones.

Table I reports market capitalization (value of tradable shares) and total capitalization (including non-tradable shares). The difference between the two reflects the presence of non-tradable shares. Over time, SHSE's market capitalization grew from 0.65 trillion yuan in 2005 to 29.92 trillion yuan in 2019, while SZSE's market capitalization increased from 0.35 trillion yuan to 18.19 trillion yuan during the same period. The ratio of tradable shares also rose significantly, from less than 40% in 2005 to over 75% by 2019, reflecting the progress of the state share reform.

Additionally, Table I reports the annual turnover rates for both exchanges during the sample period. Both exchanges exhibit exceptionally high turnover rates, with SHSE ranging from 123% in 2012 to 559% in 2008, and SZSE ranging from 321% in 2012 to 749% in 2015. It is worth noting that SZSE tends to list smaller-cap stocks, which typically exhibit higher turnover rates, contributing to its higher turnover rates.

Inspired by the well-documented medium-term price momentum in the U.S. stock market, we first apply the portfolio sorting methodology developed by Jegadeesh and Titman (1993) to analyze price momentum and reversals across monthly, weekly, and daily horizons. Table II presents the results for monthly returns. Stocks are sorted based on their past one-, three-, six-, and twelve-month returns, and long-short portfolios (both value-weighted and equal-weighted) are constructed. The future one-month returns for these portfolios are consistently negative, indicating price reversals rather than momentum. This finding corroborates the absence of medium-term price momentum in the Chinese stock market, as previously highlighted by Chui et al. (2010) and Du et al. (2022)..

We extend this analysis to weekly horizons in Table III, where stocks are sorted based on past returns over one to eight weeks. The subsequent weekly returns of these portfolios again show price reversals rather than momentum, regardless of whether value-weighted or equal-weighted sorting is employed. These results further reinforce the dominance of price reversals at medium-term horizons in the Chinese market.

Table IV presents the results of portfolio sorting for daily returns. Stocks are sorted based on their returns over the past one to ten days, and we report the returns of long-short portfolios for the subsequent one to ten days. As shown in Panel A, there is a pronounced momentum effect in daily stock returns, which persists for one day before reversing. For instance, a long-short portfolio sorted by returns from the previous day yields a one-day return of 0.37%. This magnitude is striking—when annualized (multiplying by 250 trading days), it translates to an impressive annual return of 92.5%.

It is important to recognize that transaction costs and microstructure effects inherently work against the detection of price momentum. A well-documented phenomenon, the bid-ask bounce, introduces negative serial correlation in daily stock returns (e.g., Roll (1984)). This effect directly counteracts any momentum patterns in daily returns. Therefore, the significant price momentum identified in our analysis is particularly noteworthy. For such momentum to be observed, the underlying price momentum in daily returns must be sufficiently robust to offset the negative serial correlation caused by the bid-ask bounce effect.

The momentum in daily returns reverses quickly. Holding the long-short portfolio for two days results in a cumulative return of 0.30%, indicating a mild reversal beginning on the second day. Extending the holding period further leads to even lower cumulative returns. These patterns of daily price momentum followed by rapid reversals are consistent across both value-weighted and equal-weighted portfolios, underscoring the robustness of these findings.

The Chinese stock market enforces a 10% limit on daily price changes for individual stocks, as studied by Chen et al. (2019). If a stock's price moves beyond this threshold in either direction, trading is suspended for the remainder of the day and resumes on the next trading day with the price limit reset. These daily price limits may mechanically induce a continuation of stock prices after hitting the limit. To address this potential issue, we exclude stock-day observations where returns hit either the upper or lower daily price limits and present the results in Panel B of Table IV.

The magnitude of return continuation decreases by more than half, highlighting the substantial contribution of price limits to daily momentum, as expected. However, the daily momentum effect remains both statistically and economically significant. This finding confirms that the observed daily price momentum is not solely a byproduct of price limits. It persists even in the absence of limit-triggered returns, pointing to underlying structural forces driving price dynamics beyond the mechanical effects of daily price limits.

In summary, our findings confirm the absence of price momentum in both monthly and weekly stock returns. More notably, we identify a significant price momentum effect in daily stock returns, where stocks with higher returns today are likely to outperform on the following day. However, this continuation pattern reverses within a few days. Additionally, we observe consistent price reversals over longer horizons, spanning one week to twelve months.

In the next section, we leverage account-level transaction data from the Shenzhen Stock Exchange to analyze how different investor groups react to past returns and to investigate the relationship between the observed daily price momentum and the trading activity of new investors.

II. New Investors and Daily Momentum

Reopened in the early 1990s, the Chinese stock market is a distinctive ecosystem dominated by retail investors and characterized by a steady influx of new participants—a hallmark of emerging markets. These new investors, often lacking investment experience, are particularly susceptible to cognitive biases and the emotional swings induced by market volatility.

In this section, we utilize granular account-level data from the Shenzhen Stock Exchange (SZSE) to classify investors into distinct groups and analyze their trading activities. This comprehensive dataset offers a unique perspective on how daily price momentum is influenced by the behaviors of new investors and other investor groups. The SZSE is one of China's two major stock exchanges. As noted by Allen et al. (2020), the Shanghai Stock Exchange (SHSE) predominantly lists state-owned enterprises and larger firms, while the SZSE specializes in private and smaller companies. With its strong emphasis on technology firms, the SZSE is often likened to the Nasdaq in the U.S. stock market.

As summarized in Table I, the SZSE surpassed the SHSE in the number of listed stocks after 2010 and consistently exhibits significantly higher turnover rates. These elevated turnover rates reflect the exchange's focus on smaller, more speculative stocks, which attract substantial retail investor participation. This distinctive characteristic makes the SZSE particularly well-suited for examining trading dynamics and the formation of price momentum.

Unlike many global markets, Chinese regulations require brokerage firms to disclose the associated brokerage accounts involved in every transaction directly to the stock exchange. This contrasts sharply with practices in most other countries, where stock exchanges lack visibility into the identities of trading accounts. At the SZSE, individual retail accounts are uniquely identified using the national ID of the account holder. This system allows for the consolidation of transaction records across multiple accounts held by the same individual, even when these accounts span different brokerage firms.[2] This meticulous record-keeping enables precise tracking of individual trading behaviors, including those of new investors.

Using this data, we categorize all accounts into three retail investor groups and two institutional investor groups over the period from 2005 to 2019. Retail investors with account balances exceeding three million yuan are classified as large investors, labeled as (L). The remaining accounts with balances below three million yuan are further divided into two groups based on account age: new investors (New), with account ages of less than three months, and general retail investors (Gen), with account ages exceeding three months. This framework segments the retail investor population into three categories: New, Gen, and L.[3]

The group of investors with more than three months of experience and account balances below three million RMB represents the majority of retail investors, while large investors are generally regarded as more sophisticated participants in the Chinese stock market.[4] These groups serve as benchmarks for assessing and comparing the behavior of new investors.

Institutional investors are classified into two groups: mutual funds (MF) and other institutions (OI).

A. New Investors as Noise Traders

In this subsection, we present summary statistics and a preliminary analysis to compare new investors with other investor groups, emphasizing new investors as a representative group of noise traders.

Panel A of Table V provides demographic information, comparing the average age of new investors to that of all retail investors over time. The data reveal that new investors are

[2]Since April 13, 2015, Chinese investors have been permitted to maintain multiple accounts with various brokerage firms.

[3]Some large retail investor accounts may also be newly opened, but this subset is small and does not warrant further subdivision by account age.

[4]Chen et al. (2019) found that investors with large accounts often front-run smaller investors before stocks hit daily price limits. Their study identifies large accounts using a higher threshold of 10 million RMB, resulting in a smaller subset of large investors than defined in our study.

consistently younger than the average retail investor, a trend that persists throughout the sample period. Regarding gender composition, also shown in Panel A, male investors are slightly more prevalent among both new and overall retail investors. However, the gender distribution between these groups shows no significant differences.

Panel B reports the turnover rates of new investors, comparing their average daily turnover rates to those of other investor groups.[5] Consistent with the well-documented high trading intensity of Chinese investors, as reviewed by Liu et al. (2022), all three retail groups exhibit exceptionally elevated daily turnover rates. New investors show the highest trading activity, with an average daily turnover rate of 18.12%, corresponding to an astonishing annual rate of approximately 4,500%. While lower, the daily turnover rates of general and large investors—8.03% and 3.26%, respectively—are still significantly higher than the trading activity typically observed among the U.S. retail investors, as highlighted by Odean (1999).

At the aggregate market level, we calculate the proportion of new investors each month, scaled by the total number of active investors in the SZSE, denoted as ($frac\_ni$). At the individual stock level, for each of the five investor groups, we compute *Netbuy*, defined as the total value of purchases minus sales by a group over a month, normalized by the stock's float capitalization from the prior month. Additionally, we gather stock-level data from the CSMAR database, including shares outstanding, trading volume, distribution events, and floating capitalization, along with firm-level accounting information such as book equity, earnings, sales, and investment for further analyses.

The definitions of the variables used in this section are provided in the Appendix. Table A1 of the Internet Appendix summarizes the key statistics of these variables. Panel A presents summary statistics for the entire SZSE market over time. Panels B and C provide statistics for stock-level analyses, covering all A-share stocks traded on the SZSE at monthly and daily frequencies, respectively.

The average fraction of new investors during the sample period is 3.7%. However, this

[5]The SZSE provided only the most recent turnover summary for 2019.

figure exhibits significant temporal variation, as illustrated in Figure I. From 2005 to 2019, the ratio of new investors (*frac_ ni*) undergoes pronounced cycles, with two notable surges in 2007 and 2015, corresponding to the two largest market booms in the history of the Chinese stock market. A clear pattern emerges: market booms are accompanied by sharp increases in new investor entries, while market collapses coincide with rapid declines in new account openings.[6]

To evaluate the stock selection abilities of different investor groups, we analyze the return predictability of each group's trading activity over monthly horizons. Specifically, we perform Fama-MacBeth regressions of future one-month stock returns on the *Netbuy* variable for each investor group. Table VI presents the results.

Column (1) shows that the net buying by new investors significantly predicts negative returns, indicating that stocks purchased by new investors tend to underperform in the subsequent month. The effect is also economically significant: a one-standard deviation increase in $Netbuy(New)$ is associated with a 1.73% (= 0.347% $\times$ 5.0) decrease in the next-month returns.

Column (2) reveals that the *Netbuy* of general retail investors (*Gen*) similarly predicts negative returns: a one-standard-deviation increase in their *Netbuy* is linked to a 0.96% (= 0.032% $\times$ 30.6) decline in next-month returns. Despite their greater experience in trading, this group also tends to select underperforming stocks.

Columns (3), (4), and (5) highlight a stark contrast. The net buying of large retail investors (L, with account balances exceeding three million RMB), mutual funds, and other institutional investors positively predicts future one-month returns. A one-standard-deviation increase in *Netbuy* for these groups corresponds to increases in next-month returns of 0.63% (= 0.038% $\times$ 16.5), 0.21% 0.46% (= 0.021% $\times$ 22.0) and 0.31% (= 0.018% $\times$ 17.5), respectively. These findings suggest that these groups possess stronger stock selection abilities compared

[6] Supplementary analysis in Table A2 of the Internet Appendix shows that the ratio of new investors (*frac_ ni*) has significant negative predictive power for market returns over the subsequent 1, 3, 6, and 12 months, highlighting the poor market timing of new investors.

to new and general retail investors.

Additionally, several stock-level control variables exhibit predictive power for future returns. The coefficients suggest that small-cap, low-turnover, and value stocks tend to outperform large-cap, high-turnover, and growth stocks. A significant one-month return reversal effect is also observed. Furthermore, stocks with high maximum daily returns or high liquidity are associated with lower future one-month returns. These findings align with the results reported by Liu et al. (2019) on the cross-section of stock returns in China.

In Panels A to C of Table A3 in the Internet Appendix, we present results for predicting subsequent three-, six-, and twelve-month returns. The findings are consistent across longer horizons: the *Netbuy* of both new and general investors significantly predicts negative future returns over three, six, and twelve months, with the magnitudes increasing over longer periods. Conversely, the *Netbuy* of large investors positively predicts future returns over these same horizons. Panels D to G further report estimations using DGTW-adjusted stock returns. All results remain robust, confirming the consistency of these patterns across various return measures and time horizons.

In summary, new investors exhibit the highest turnover rates and the poorest stock selection skills among all investor groups. However, general retail investors with more than three months of experience also engage in frequent trading and show subpar stock selection abilities, although to a lesser extent than new investors. In contrast, the remaining three groups—large retail investors, mutual funds, and other institutions—consistently exhibit strong stock selection capabilities, with large retail investors standing out as the most adept.[7]

In Figure II, we break down the contributions of the five investor groups to overall trading volume. Despite their high turnover rate, new investors account for only 2.01% of total trading volume, a modest contribution attributable to their limited market share. In

[7]Extensive evidence highlights large retail investors as sophisticated traders in the Chinese stock market. For instance, Chen et al. (2019) analyze market dynamics around the 10% daily price limits and find that large investors tend to purchase stocks just before they hit the limit, subsequently selling them to smaller investors the following day for a profit. Similarly, An et al. (2022) document how the 2014–2015 boom-and-bust cycle in the Chinese stock market exacerbated wealth disparities between large and small retail investors.

contrast, general retail investors dominate trading activity, contributing 65.4% of the total volume, reflecting their larger presence in the market.

It is important to note that the distinction between new and general investors is based on an arbitrary cutoff of three months of trading experience. As such, new investors serve as an amplified subset of noise traders, representing the high-turnover and low-performance characteristics commonly associated with this group.

B. Reactions of Different Groups to Past Returns

The behavioral finance literature identifies several cognitive biases among investors as potential drivers of price momentum, including extrapolative beliefs (e.g., Barberis et al. (1998) and overconfidence (e.g., Daniel et al. (1998)). New investors, being less experienced and more susceptible to market fluctuations, are particularly prone to these biases compared to other investor groups. In this section, we analyze how different investor groups trade in response to past stock returns. Our focus is on daily trading activity, allowing us to directly link their behavior to observed daily price momentum.

Specifically, we regress the *Netbuy* of a stock by each investor group $Netbuy_{i,d+1}$ on three non-overlapping past returns of the stock: the last-day return ($Ret_{i,d}$), the past week return excluding the last day ($Ret_{i,d-5\to d-1}$), and the past month return excluding the last week ($Ret_{i,d-21\to d-6}$). The regression model is specified as follows:

$$Netbuy_{i,d+1} = Constant + c_1 Ret_{i,d} + c_2 Ret_{i,d-5\to d-1} + c_3 Ret_{i,d-21\to d-6} + Controls_{i,d} + \epsilon_{i,d+1}. \quad (1)$$

The control variables include size (Ln_cap), book-to-market ratio (BM), and turnover rate ($Turnover\_float$).

Table VII shows that the five investor groups exhibit distinctly different responses to past returns. As anticipated, Column (1) reveals that new investors act as momentum traders—their *Netbuy* displays a significant positive response to both the past day's return and the past week's return, while showing a negative, though statistically insignificant, reaction to the past month's return. These findings highlight that new investors are highly reactive to past returns at a daily frequency, with their reactions reversing direction within a month. This rapid reaction frequency explains why price momentum in this market operates on a much shorter time scale compared to more developed markets.

In contrast, Columns (2) and (3) indicate that general and large retail investors behave as contrarian traders. Their *Netbuy* responds negatively to returns across all three time horizons, except for the insignificantly positive reaction of large investors to the past week's return.

Column (4) also reveals that mutual fund investors collectively exhibit momentum trading behavior, with uniformly and significantly positive responses to past day, past week, and past month returns. In contrast, the reactions of the fifth group, other institutions, as shown in Column (5), are more ambiguous. While their responses to past day and past month returns are statistically insignificant, they display a significantly positive reaction to past week returns.

The reaction to the past day's return is particularly noteworthy in understanding the mechanisms driving daily price momentum. Table VII shows that new investors and mutual funds both exhibit positive reactions to the past day's return, whereas general and large investors take opposing, contrarian positions. While it is somewhat expected for large investors to trade counter to new investors, it is surprising to observe mutual funds—known for their stock selection capabilities—aligning with new investors by chasing past returns rather than opposing them. This trading pattern suggests that mutual funds may employ a strategy distinct from that of large investors. Additionally, the stark contrast between the responses of general retail investors and new investors to the past day's returns is unexpected. However, it is worth noting that the general investor group includes a diverse range of retail participants, potentially obscuring more nuanced behavioral patterns within the aggregate group.[8]

[8] To address the concern that daily price limit events might disproportionately attract certain investor groups, particularly inexperienced and new investors, we reanalyze the reactions of the five investor groups

C. Which Group Drives Daily Price Momentum?

The analysis in the preceding subsection revealed that both new investors and mutual funds exhibit positive reactions to the past day's return. But does the trading activity of these groups drive the observed daily price momentum? For a group's trading to act as a catalyst for daily momentum, we would expect the group's current trading activity, in response to a stock's past day return, to amplify the stock's current day return. In other words, there should be a positive correlation between the stock's current day return and the interaction between its past day return and the group's current day trading. Furthermore, this interaction should also be linked to a subsequent price reversal in the stock.

We use this strategy to analyze how the observed daily price momentum is influenced by the trading of each investor group. Specifically, we employ the following regression model:

$$\begin{aligned} Ret_{i,d+1} =& Constant + c_1 Ret_{i,d} + c_2 Netbuy_{i,d+1} + c_3 Ret_{i,d} \times Netbuy_{i,d+1} \\ &+ c_4 Ret_{i,d-5\to d-1} + c_5 Ret_{i,d-21\to d-6} + Controls_{i,d} + \epsilon_{i,d+1}. \end{aligned} \tag{2}$$

The key variable of interest is the interaction term $Ret_{i,d} \times Netbuy_{i,d+1}$, which captures the extent to which an investor group's trading activity in response to the past-day return $Ret_{i,d}$ affects the stock's current day return at $d+1$. As in previous regressions, we include control variables for firm size (*Ln_ cap*), book-to-market ratio (*BM*), and turnover rate (*Turnover_float*).

Table VIII reports the regression results for all investor groups. Panel A focuses on new investors. Column (1) reveals a significant and positive relationship between a stock's current day return and the interaction between its past day return and new investors' current day trading of the stock. In Columns (2) and (3), we replace the dependent variable in Equation (2) with returns over trading days 2 to 6 and days 2 to 11, respectively. The results indicate

while excluding instances of hitting daily price limits. The results, presented in Table A4 in the Internet Appendix remain consistent with those in Table VII.

that this interaction term tends to exhibit a significantly negative relationship with the stock's subsequent one- and two-week returns. These findings provide consistent evidence that the trading activities of new investors, driven by the past day's returns, are correlated with both the observed daily price momentum and the subsequent price reversal.[9]

To account for days when a stock hits the 10% daily price limits, we include additional control variables: two dummies, Hit_i^U, d and Hit_i^D, d, indicating whether the stock hits the up or down price limit, respectively, along with their interactions with new investors' net buying activity, $Netbuy_{i,d+1}$. We report the regression results in Panel A, Columns (4)–(6), where the dependent variable is the stock return over the current day, trading days 2 to 6, and trading days 2 to 11, respectively.

The coefficient of the key interaction term between a stock's past day return and new investors' current day trading remains highly significant and consistent with the results in Columns (1)–(3), although the magnitudes are somewhat attenuated. Overall, these findings confirm that, irrespective of whether the stock hits the daily price limits, new investors' trading activity is strongly associated with the current day price momentum and subsequent price reversal.

Panel B presents the regression results for general retail investors, denoted as *Gen*. Notably, the interaction between a stock's past day return and general investors' current day trading activity exhibits a positive correlation with the stock's current day return and a negative correlation with its subsequent one- and two-week returns. This pattern holds consistently, whether the hitting of daily price limits is not controlled (columns (1)-(3)) or controlled (columns (4)-(6)). These statistically significant correlations indicate that general

[9] In Table A5 of the Internet Appendix, we use a portfolio sorting approach to further investigate the link between new investors' trading activity and the daily momentum effect. Stocks are sorted into quintiles based on past one-day returns and terciles based on the ratio of trading volume by new investors to total trading volume over the last 22 trading days. For each portfolio, we calculate the one-day return, weighted either by recent market capitalization or equally. Consistent with our regression analyses, we find an amplified daily momentum effect for stocks heavily traded by new investors. Both "winner" and "loser" portfolios exhibit significant price continuations into the next day, with stronger momentum observed in stocks predominantly traded by new investors. These results highlight the crucial role of new investors in reinforcing price momentum in daily stock returns.

investors' trading, in reaction to the past day's return, plays a role in driving both the observed daily price momentum and the subsequent price reversal.

This result is somewhat surprising, given that this group generally exhibits a negative response to the past day's return, as discussed in the preceding subsection. We hypothesize that this could be attributed to the heterogeneity within the group classified as general investors. Given the broad definition of this category, it is likely that some investors in the group barely meet the threshold of three months of trading experience and may display trading behaviors similar to those of new investors. The activity of these relatively inexperienced members within the group may help drive the observed daily momentum, despite the overall negative reaction of the group to the past day's return.

Panels C to E examine the relationship between daily price momentum and the trading activities of large retail investors (L), mutual funds (MF), and other institutions (OI), respectively. A consistent pattern emerges across the regression results for all three groups: the interaction between a stock's past day return and each group's current day trading activity is positively correlated with the stock's current day return and negatively correlated with its subsequent one-week and one-month returns. All these relationships are statistically significant, suggesting that these groups contribute to both the counteraction of daily price momentum and the subsequent price reversal.

The role of mutual funds in counteracting daily price momentum is particularly unexpected, given their previously discussed positive response to the past day's returns. This finding implies that, although mutual funds tend to buy recent winners, their trading does not fuel further price continuation and instead contributes to eventual reversals. This outcome is consistent with prior observations that mutual funds exhibit significant stock selection ability.

In Table A6 of the Internet Appendix, we present additional results from the Fama-MacBeth regressions of new investors' *Netbuy* on the *Netbuy* of other investor groups. The findings confirm that, across different stocks, the trading activities of new investors exhibit a significant and positive correlation with those of general retail investors. Conversely, significant and negative correlations are observed with the trading activities of large retail investors, mutual funds, and other institutions. These relationships align with the differing contributions of new investors and other groups to the observed daily price momentum.

In Panel F, we incorporate four investor groups—new investors (*New*), general investors (*Gen*), large retail investors (*L*), and mutual funds (*MF*)—into the same regressions to perform a comparative analysis of their effects in a "horse race." As shown in Figure II, the contribution of other stakeholders (such as blockholders, insiders, etc.) to trading volume is negligible. Therefore, we exclude other institutions (*OI*) from these regressions to avoid multicollinearity.

In Columns (1)–(3), the interaction between new investors' current day trading and the stock's past day's return remains significantly correlated with both daily price momentum and subsequent reversal. This pattern is fully consistent with the results in Panel A, which excludes the net buying of other groups, confirming the robustness of this relationship in the horse race analysis. In Columns (4)–(6), when controls for hitting daily price limits are included, the pattern persists, though with somewhat reduced coefficient magnitudes and t-statistics.

The *Netbuy* of general investors exhibits similar patterns to that of new investors, though with much smaller impacts on price dynamics. In contrast, the trading influences of other groups, such as large retail investors and mutual funds, display opposing patterns to those of new investors. These results align with the findings from earlier panels analyzing individual groups, although some coefficients lose statistical significance in the multi-group setting. Overall, these findings highlight the distinctive and robust contributions of new investors, along with general retail investors, to the observed daily price momentum and subsequent price reversal.

In conclusion, Table VIII highlights that new investors and general retail investors play significant roles in driving daily price momentum and subsequent price reversals. In contrast, the other three groups—large investors, mutual funds, and other institutions—tend to counteract these price effects. The contribution of new investors is particularly robust and pronounced. Accordingly, we attribute the observed price momentum primarily to the trading behavior of new investors, alongside certain individuals within the general investor group whose trading patterns resemble those of new investors.

D. Price Momentum across Different Market Conditions

Why do new investors in China exhibit such a swift reaction to daily stock returns? This rapid response contrasts sharply with the slower frequency of monthly price momentum observed in more mature markets, such as the U.S. stock market. Casual observations suggest that this quick reaction stems from the intense focus Chinese investors, particularly new ones, place on tracking stock market fluctuations. The emotions triggered by gains and losses from these fluctuations appear to be especially engrossing for new investors, who often lack the experience and discipline to separate stock trading from other activities. This observation aligns with numerous reports of investors spending excessive time monitoring, deliberating, and trading stocks. The extraordinarily high turnover rate among new investors further underscores their intense engagement with the stock market.

Due to the absence of direct data measuring investor attention to the stock market, we adopt an indirect approach to investigate whether the observed daily price momentum is linked to investor attention. The existing literature on investor attention, such as Sicherman, Loewenstein, Seppi, and Utkus (2016), suggests that retail investors are more likely to focus on the market following positive returns. Therefore, we hypothesize that the daily price momentum driven by new investors will be more pronounced during periods of elevated market returns, when new investors are likely to be paying closer attention to the stock market.

In Table IX, we examine variations in new investors' trading behavior under "Market Up" and "Market Down" conditions. "Market Up" days are defined as those when the daily market return exceeds the median of daily returns over the sample period, while "Market Down" days are those when it falls below the median.

Specifically, Columns (1) and (2) analyze the relationship between new investors' *Netbuy* and returns over the past day, past week, and past month, distinguishing between "Market Up" and "Market Down" conditions. As expected, new investors' trading is more sensitive to the past day's return during "Market Up" conditions. Moreover, their responses to past week and past month returns are also amplified under "Market Up" conditions.

In Column (1), the coefficient on $Reti, d-5 \rightarrow d-1$ is significantly positive during "Market Up" conditions but becomes insignificant in Column (2) for "Market Down." Similarly, the coefficient on $Reti, d-21 \rightarrow d-6$ remains positive but insignificant during "Market Up" and turns significantly negative during "Market Down." These results suggest that new investors adapt their trading strategies more rapidly during declining market conditions.

In Columns (3) and (4), we control for whether the current day's return hits the 10% daily price up or down limits. The results remain consistent: new investors respond positively to past-day returns, with their responsiveness intensifying during "Market Up" conditions. These findings suggest that new investors are more inclined to follow daily price trends in favorable market conditions than during downturns.

In the next section, we turn our attention to international markets, systematically analyzing the daily price momentum effect across major developed and emerging markets worldwide. While trading data specific to new investors is unavailable for these markets, we examine differences in price momentum between bullish ("up") and bearish ("down") market conditions. Building on the findings from Table IX, we anticipate observing asymmetric patterns, consistent with the presence of price momentum and heightened investor enthusiasm during bullish conditions.

III. Daily Momentum in International Markets

Is daily price momentum a phenomenon unique to the Chinese stock market, or does it transcend borders to manifest in other global markets? In this section, we explore the prevalence of daily momentum across major emerging and developed markets, focusing on its presence and its asymmetric behavior during bullish and bearish periods. Bid-ask bounce, as noted by Roll (1984), can induce negative serial correlations in daily returns, and the wider bid-ask spreads typical of emerging markets might initially suggest greater difficulty in identifying daily price momentum within these markets.

Our analysis draws on DataStream's extensive international stock return database, spanning 1980 to 2023. Covering over 100,000 stocks from nearly 200 countries, DataStream offers unparalleled breadth, though concerns about potential data inaccuracies have been raised in previous literature. To address these, we employ a winsorizing approach, capping raw returns at the top and bottom 2.5% for each day and each exchange. Following Hou, Karolyi, and Kho (2011) and Ince and Porter (2006), we further exclude observations with missing data or zero daily returns, acknowledging DataStream's practice of repeating prior data for delisted firms.

For emerging markets, we consolidate two widely recognized lists from Fama and French (2012) and Karolyi and Wu (2018). This results in a comprehensive initial roster of 27 emerging markets beyond China. However, to ensure analytical robustness, we restrict our sample to markets with at least 100 stocks for a continuous five-year period, yielding a final set of 21 emerging markets, including Brazil, Chile, China, Czech Republic, Egypt, Greece, India, Indonesia, Israel, Malaysia, Mexico, Pakistan, Philippines, Poland, Saudi Arabia, South Africa, South Korea, Taiwan, Thailand, Turkey, and Vietnam.

For comparison, we apply the same criteria to developed markets, producing a final sample of 21 economies, including Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong, Italy, Japan, the Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, the United Kingdom, and the United States. Table A7 of the Internet Appendix provides a detailed overview of the sample, including the number of stocks, sample periods, and market capitalizations for each market in our sample.

To assess the potential impact of daily price limits—which may restrict price movements and mechanically create daily price momentum—we gather data on such policies across the international markets in our sample. A detailed overview of these policies and their sources is provided in Table A8 of the Internet Appendix. We define daily price limits specifically as policies that cap the maximum allowable daily price movement, excluding mechanisms like "circuit breakers," "trading pauses," or "volatility interruptions," which permit further price fluctuations following a halt.

The data reveal that daily price limit rules are predominantly implemented in emerging markets, with 14 of the 21 markets in our sample adopting such measures over the past decade. By contrast, Japan stands alone among developed markets in enforcing daily price limit policies.

For each market, stocks are sorted daily into quintiles based on their returns. The next day's portfolio return is then calculated, using either value-weighting based on the previous month's market capitalization or equal-weighting. We evaluate the performance of a long-short momentum strategy, which involves taking a long position in the top quintile and a short position in the bottom quintile. To ensure statistical robustness, we use Newey-West standard errors with a 21-day lag.

Table X presents the daily returns of the momentum portfolios across the markets in our sample. Among the 21 developed markets, only Austria, the Netherlands, and the U.K. exhibit significantly positive value-weighted daily momentum returns. Notably, the U.K. is the sole developed market with significant equal-weighted momentum. By contrast, reversals dominate developed markets, with 16 displaying significant value-weighted reversals, a figure that rises to 19 under equal-weighting. These reversal patterns align closely with the bid-ask bounce effect.

In stark contrast, daily price momentum is far more prevalent in emerging markets. Of the 21 emerging markets, 14 demonstrate significantly positive value-weighted daily momentum, including Chile, China, Czech Republic, Egypt, Greece, Israel, Mexico, Pakistan, Saudi

Arabia, South Africa, South Korea, Taiwan, Turkey, and Vietnam. Furthermore, 10 of these markets show significant equal-weighted momentum patterns. Conversely, six emerging markets exhibit value-weighted reversals, increasing to 10 under equal-weighting. The prevalence of daily momentum in emerging markets is particularly notable, given their higher bid-ask spreads, which might be expected to suppress such patterns.

Panel A of Table X identifies whether each market has implemented daily price limit rules over the past decade. Panel B summarizes the findings: among emerging markets without price limits, six out of seven exhibit significant equal-weighted momentum, and five show value-weighted momentum. This persistence suggests that daily momentum effects are not merely mechanical artifacts of price limit policies.

In the 14 emerging markets with daily price limits, eight display value-weighted momentum, and six exhibit equal-weighted momentum. These results indicate that price limit policies are neither a necessary nor sufficient condition for the emergence of daily momentum, highlighting the influence of broader market dynamics.

In developed markets, the limited instances of daily momentum occur exclusively in those without price limits. Japan, the only developed market with price limit policies, instead exhibits daily reversals, aligning with the broader reversal patterns seen in advanced economies.

These findings underscore that daily price momentum cannot be solely attributed to the presence or absence of price limit policies. Instead, they emphasize the importance of structural and behavioral factors in shaping market outcomes, particularly in emerging markets.

The lack of granular trading data and investor identity information in international markets limits our ability to directly examine the role of new investors in driving daily price momentum. Instead, we focus on analyzing a key implication: the asymmetric patterns of daily momentum during bullish versus bearish market conditions. This approach is inspired by our earlier findings from the Chinese stock market, where heightened trading activity among new investors is particularly evident in bullish phases.

As shown in Table XI, we present results for markets exhibiting daily price momentum, segregated by periods when market returns are above the median ("Market-up") and below the median ("Market-down"). The findings reveal a consistent asymmetry: daily momentum is significantly stronger during bullish conditions than bearish ones, regardless of whether value-weighted or equal-weighted metrics are employed. These results align with the patterns previously observed in China.

In summary, daily price momentum is a widespread phenomenon, extending beyond the Chinese stock market. It is particularly prominent in emerging markets, with nearly half of the sampled markets displaying this effect, whereas developed markets predominantly exhibit daily return reversals. Among emerging markets with daily momentum, an asymmetric pattern between bullish and bearish periods is evident, reinforcing the idea that new investor activity might be a key driver. Importantly, the daily price limit rules common in emerging markets do not fully explain these momentum patterns, further highlighting the potential influence of investor behavior as a central factor.

IV. Conclusion

In this paper, we document a new phenomenon: daily price momentum in the Chinese stock market. Our international sample, comprising 21 emerging markets and 21 developed markets, reveals that approximately half of the emerging markets exhibit significant daily price momentum effects, whereas developed markets are more likely to display daily reversal patterns.

Leveraging account-level data from the Shenzhen Stock Exchange (SZSE) in China, we classify investors into five groups, including a distinct group of new investors with no prior stock trading experience. By analyzing the net buying behavior of each investor group in response to past stock returns, we find that new investors and general retail investors with account balances below three million yuan significantly drive daily price momentum and subsequent price reversal. In contrast, other groups—large retail investors, mutual funds, and other institutions—act to counterbalance these price effects. The contribution from new investors is particularly notable and pronounced.

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Appendix: Variable definitions

Market-wide time series:

Frac_ni: the number of new investors divided by the number of active investors in the Shenzhen stock exchange

Mkt_ret: market return, which is calculated as the value-weighted average return of stocks in both Shanghai and Shenzhen Stock Exchange

Mkt_vol: value-weighted average stock volatility (annualized). Stock volatility is the standard deviation of stock daily returns within the month

Mkt_turnover: the value-weighted average stock turnover rate. Stock turnover rate equals the number of shares traded divided by floating capitalization

Mkt_bm: the value-weighted average of stocks' book-to-market ratio

Stock level cross section, monthly:

Netbuy: the total value of purchase minus sales by certain investor group over a month, divided by the stock's float cap in the previous month

Retail: all retail investors

New: the group of new investors with account value lower than 3M RMB

Gen: the group of investors with account value lower than 3M RMB but not new investors

L: the group of investors with account value high than 3M RMB

MF: mutual funds

OI: Institutional investors that are not mutual funds

Ret: stock monthly return adjusted for splits and dividends

Ret_dgtw: stock return minus benchmark return, which is the average returns of stocks in the same 5x5x5 buckets based on size, BM, and past 12-month return

Ln_cap: the log of one plus the stocks floating capitalization, which equals number of tradable shares times the price

BM: the most recent year-end book equity divided by market capitalization

Vol: standard deviation of stock daily returns within the month

Max: the maximum daily return in the month

Turnover_float: the average daily turnover rate over the past 12 months, where daily turnover rate equals the value of shares traded divided by floating capitalization

Abn_turnover: Turnover divided by its moving average over the past 12 months

Illiq: the average ratio of absolute value of daily return to yuan volume

Stock level cross section, daily and weekly:

Defined in the same way as the monthly variables

Figure I. Fraction of New Investors over Time

This figure depicts the fraction of new accounts opened within 3 months over all existing accounts from 2005 to 2019 (dashed line). The market index over these periods is shown in dashed line.

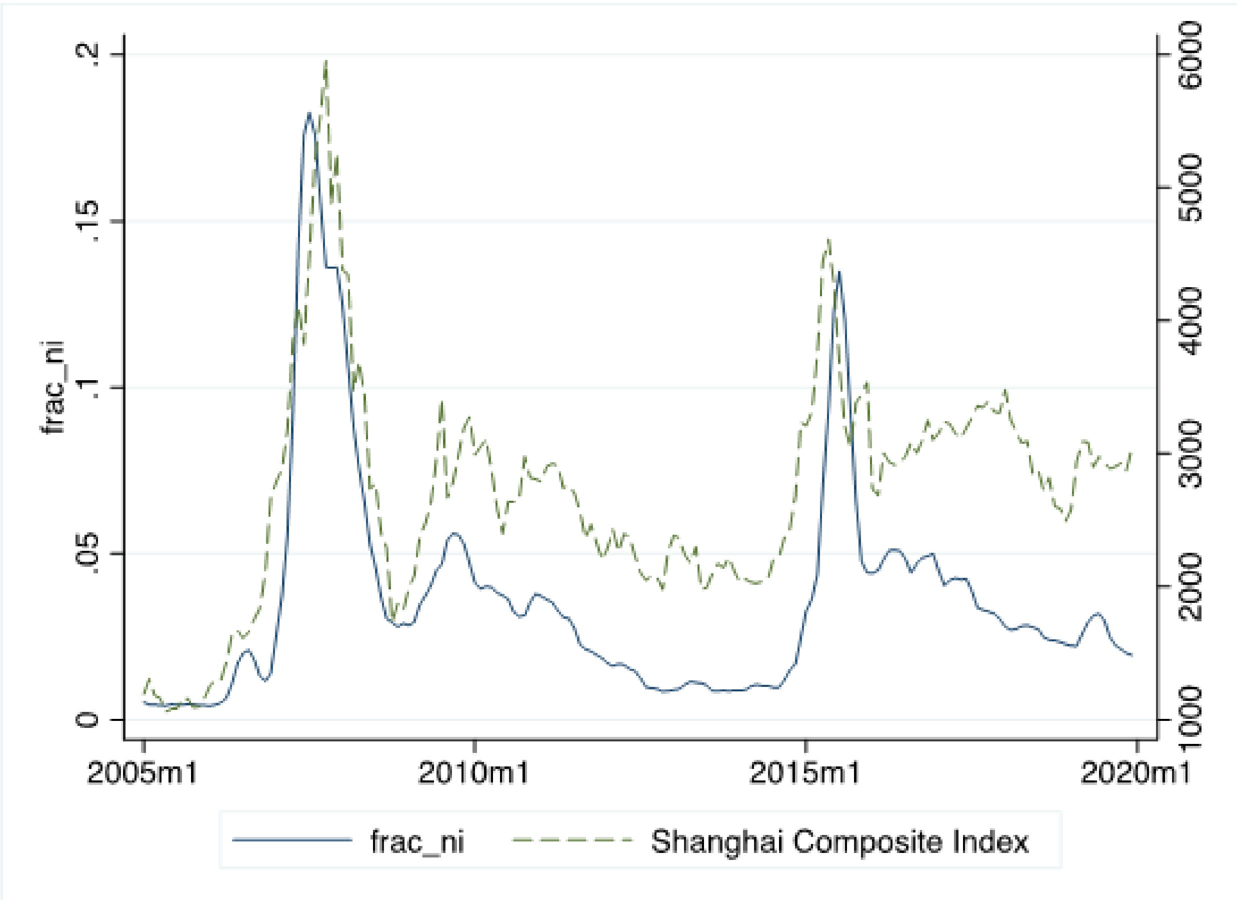

Figure II. Fraction of Trading Volume

This figure depicts the average fraction of trading volumes of six investor groups over the sample period from 2005 to 2019: new investor (*(New)*—those with retail accounts opened within the preceding three months, general retail investors (Gen)—those with less than three million RMB, and large retail investors (L)—those exceeding three million RMB, mutual fund (MF), other institutions (OI), and other investors ($Other$).

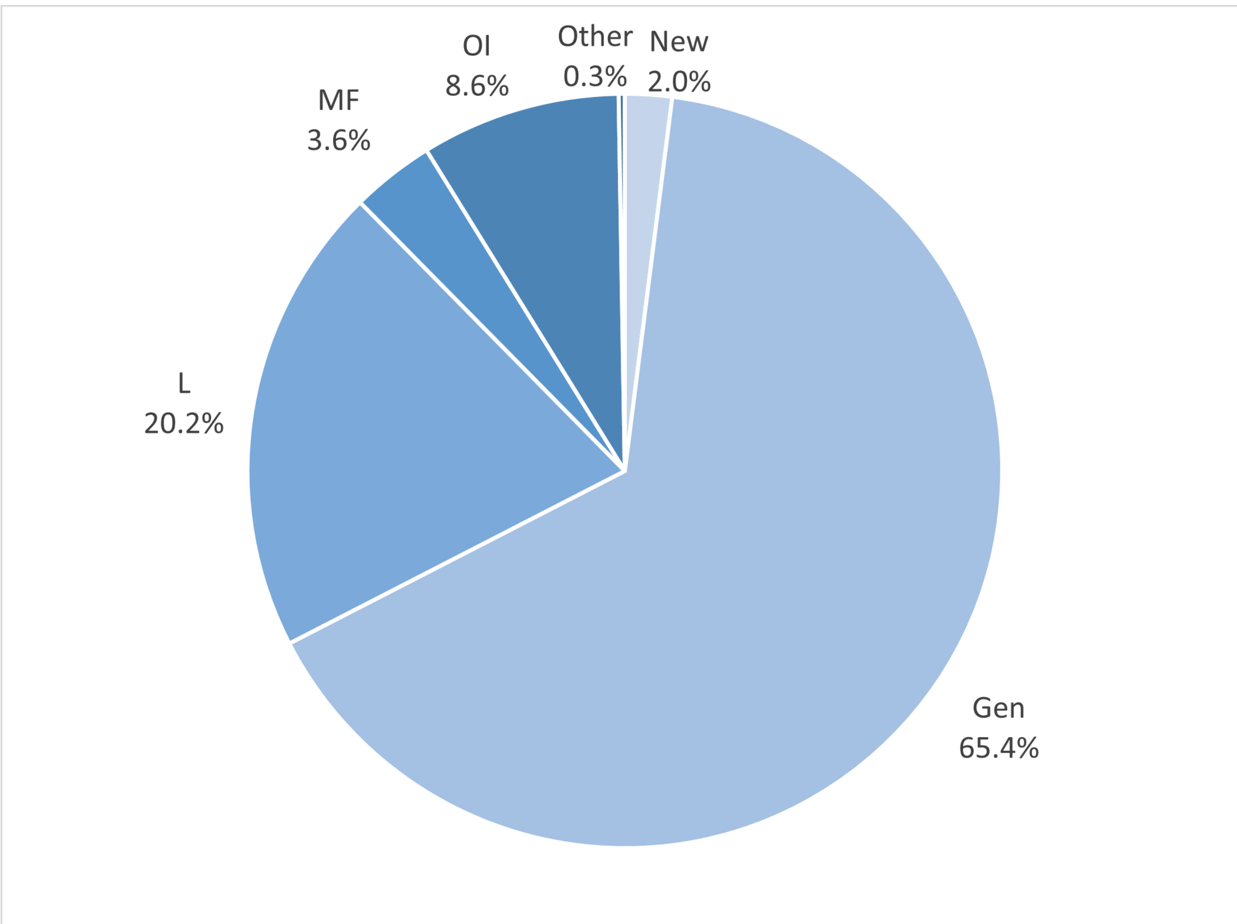

Table I. Summary of China Stock Market

This table presents the summary of the number of stocks, market capitalization (trillion yuan), total capitalization (trillion yuan), and annual turnover rate of Shanghai Stock Exchange (SHSE) and Shenzhen Stock Exchange (SZSE) from 2005 to 2009.

	SHSE				SZSE			
	Number of stocks	Market Cap	Total Cap	Turnover Rate	Number of stocks	Market Cap	Total Cap	Turnover Rate
2005	830	0.65	2.29	292%	536	0.35	0.90	343%
2006	836	1.59	7.14	360%	582	0.79	1.76	404%
2007	853	6.35	26.94	477%	664	2.74	5.63	559%
2008	852	3.21	9.76	559%	725	1.24	2.37	692%
2009	861	11.42	18.45	303%	819	3.56	5.87	530%
2010	882	14.17	17.93	214%	1138	4.95	8.51	484%
2011	919	12.24	14.85	193%	1382	4.11	6.62	445%
2012	945	13.34	15.83	123%	1511	4.64	7.07	321%
2013	945	13.59	15.07	168%	1525	6.27	8.78	377%
2014	987	22.04	24.51	170%	1605	9.41	12.78	387%
2015	1075	25.61	29.81	516%	1736	16.30	23.65	749%
2016	1175	23.86	28.43	207%	1858	15.14	22.24	509%
2017	1387	28.03	33.10	180%	2078	16.59	23.45	369%
2018	1445	23.19	26.92	173%	2125	12.00	16.47	414%
2019	1496	29.92	34.69	177%	2201	18.19	23.74	400%

Table II. Price Momentum or Reversal in Monthly Returns

This table reports results of monthly returns of sorted portfolios. We follow Jegadeesh and Titman (1993) by sorting stocks based on past returns over one, three, six, and twelve months and constructing the long-short portfolios (with both value-weighted sorting and equal-weighted sorting). t-statistics are reported in parentheses.

	Future one month return			
	Value-weight			
J: Sorting return horizon	1m	3m	6m	12m
	-0.0086	-0.0109	-0.0101	-0.0041
	(-2.11)	(-2.20)	(-1.83)	(-0.72)
	Equal-weight			
J: Sorting return horizon	1m	3m	6m	12m
	-0.0148	-0.0138	-0.0099	-0.0073
	(-5.34)	(-3.39)	(-2.47)	(-1.62)

Table III. Price Momentum or Reversal in Weekly Returns

This table reports results of cumulative returns of one to eight weeks of sorted portfolios. We follow Jegadeesh and Titman (1993) by sorting stocks based on past one to eight weeks and constructing the long-short portfolios (with both value-weighted sorting and equal-weighted sorting). t-statistics are reported in parentheses.

	I: Holding horizon							
	Value-weight							
	1w	2w	3w	4w	5w	6w	7w	8w
J: Sorting return horizon								
1w	-0.0037	-0.0023	-0.0014	-0.0030	-0.0050	-0.0080	-0.0077	-0.0065
	(-3.36)	(-1.73)	(-0.83)	(-1.57)	(-2.23)	(-2.82)	(-2.44)	(-2.21)
2w	-0.0021	-0.0002	-0.0009	-0.0033	-0.0067	-0.0076	-0.0065	-0.0054
	(-2.14)	(-0.13)	(-0.38)	(-1.17)	(-1.81)	(-1.83)	(-1.50)	(-1.28)
3w	-0.0014	-0.0014	-0.0033	-0.0070	-0.0090	-0.0097	-0.0082	-0.0077
	(-1.36)	(-0.70)	(-1.18)	(-1.89)	(-2.03)	(-2.02)	(-1.65)	(-1.54)
4w	-0.0024	-0.0037	-0.0071	-0.0102	-0.0115	-0.0116	-0.0107	-0.0099
	(-2.16)	(-1.65)	(-2.08)	(-2.40)	(-2.39)	(-2.24)	(-2.01)	(-1.86)
6w	-0.0050	-0.0075	-0.0096	-0.0113	-0.0128	-0.0132	-0.0076	-0.0125
	(-3.11)	(-2.52)	(-2.47)	(-2.58)	(-2.59)	(-2.47)	(-1.83)	(-2.16)
8w	-0.0042	-0.0056	-0.0073	-0.0094	-0.0105	-0.0111	-0.0104	-0.0111
	(-2.88)	(-2.17)	(-2.20)	(-2.36)	(-2.32)	(-2.21)	(-1.92)	(-1.88)

	Equal-weight							
	1w	2w	3w	4w	5w	6w	7w	8w
J: Sorting return horizon								
1w	-0.0051	-0.0034	-0.0036	-0.0052	-0.0072	-0.0086	-0.0091	-0.0085
	(-5.10)	(-2.58)	(-2.44)	(-3.28)	(-4.02)	(-4.24)	(-4.24)	(-4.05)
2w	-0.0040	-0.0038	-0.0058	-0.0085	-0.0112	-0.0125	-0.0123	-0.0116
	(-4.94)	(-2.77)	(-3.26)	(-3.91)	(-4.29)	(-4.36)	(-4.31)	(-4.02)
3w	-0.0044	-0.0060	-0.0090	-0.0125	-0.0149	-0.0158	-0.0153	-0.0151
	(-5.02)	(-3.69)	(-4.11)	(-4.49)	(-4.65)	(-4.67)	(-4.49)	(-4.31)
4w	-0.0054	-0.0081	-0.0117	-0.0149	-0.0167	-0.0173	-0.0172	-0.0173
	(-5.57)	(-4.41)	(-4.59)	(-4.81)	(-4.84)	(-4.78)	(-4.59)	(-4.49)
6w	-0.0064	-0.0096	-0.0125	-0.0148	-0.0165	-0.0173	-0.0125	-0.0178
	(-5.61)	(-4.61)	(-4.69)	(-4.80)	(-4.79)	(-4.61)	(-4.36)	(-4.07)
8w	-0.0056	-0.0083	-0.0108	-0.0132	-0.0148	-0.0157	-0.0158	-0.0165
	(-5.29)	(-4.38)	(-4.44)	(-4.54)	(-4.35)	(-4.06)	(-3.66)	(-3.44)

Table IV. Price Momentum or Reversal in Daily Returns

This table reports results of cumulative returns of one to ten days of sorted portfolios. We follow Jegadeesh and Titman (1993) by sorting stocks based on past returns over one to ten days and constructing the long-short portfolios (with both value-weighted sorting and equal-weighted sorting). Panel A reports the results for the full sample and Panel B for the sample excluding stock-days hitting price limits. t-statistics are reported in parentheses.

Panel A: full sample

	I: Holding horizon					
	Value-weight					
	1d	2d	3d	4d	5d	10d
J:Sorting return horizon						
1d	0.0037	0.0030	0.0031	0.0031	0.0014	0.0019
	(9.47)	(5.75)	(5.08)	(4.60)	(2.00)	(2.52)
2d	0.0017	0.0009	0.0008	-0.0005	-0.0022	-0.0011
	(5.27)	(1.90)	(1.33)	(-0.83)	(-3.13)	(-1.24)
3d	0.0012	0.0005	-0.0007	-0.0022	-0.0036	-0.0021
	(4.17)	(1.14)	(-1.21)	(-3.16)	(-4.52)	(-2.05)
5d	-0.0002	-0.0018	-0.0030	-0.0039	-0.0047	-0.0034
	(-0.63)	(-4.24)	(-5.05)	(-5.26)	(-5.43)	(-2.79)
10d	0.0001	-0.0007	-0.0013	-0.0018	-0.0023	-0.0015
	(0.37)	(-1.81)	(-2.16)	(-2.44)	(-2.52)	(-0.92)
	Equal-weight					
	1d	2d	3d	4d	5d	10d
J:Sorting return horizon						
1d	0.0038	0.0033	0.0039	0.0045	0.0029	0.0055
	(9.82)	(6.05)	(5.76)	(5.65)	(3.42)	(4.48)
2d	0.0015	0.0007	0.0008	-0.0005	-0.0020	0.0005
	(4.66)	(1.43)	(1.26)	(-0.71)	(-2.48)	(0.48)
3d	0.0008	-0.0001	-0.0014	-0.0029	-0.0040	-0.0017
	(3.06)	(-0.14)	(-2.44)	(-4.18)	(-5.13)	(-1.59)
5d	-0.0007	-0.0029	-0.0042	-0.0052	-0.0059	-0.0046
	(-3.17)	(-7.20)	(-7.84)	(-7.99)	(-7.92)	(-4.28)
10d	-0.0005	-0.0020	-0.0029	-0.0037	-0.0045	-0.0052
	(-3.06)	(-6.11)	(-6.24)	(-6.38)	(-6.36)	(-4.14)

Panel B: excluding stock-days hitting price limits

	I: Holding horizon					
	Value-weight					
	1d	2d	3d	4d	5d	10d
J:Sorting return horizon						
1d	0.0017	0.0002	0.0000	-0.0001	-0.0019	-0.0013
	(6.20)	(0.48)	(0.01)	(-0.29)	(-3.66)	(-1.95)
2d	-0.0001	-0.0015	-0.0019	-0.0034	-0.0052	-0.0041
	(-0.39)	(-3.85)	(-3.99)	(-6.27)	(-8.37)	(-4.56)
3d	-0.0003	-0.0015	-0.0030	-0.0048	-0.0061	-0.0046
	(-1.44)	(-3.96)	(-5.81)	(-7.64)	(-8.49)	(-4.45)
5d	-0.0013	-0.0035	-0.0048	-0.0058	-0.0065	-0.0051
	(-5.90)	(-8.23)	(-8.08)	(-7.80)	(-7.46)	(-3.94)
10d	-0.0007	-0.0017	-0.0022	-0.0028	-0.0032	-0.0020
	(-3.12)	(-3.93)	(-3.58)	(-3.58)	(-3.37)	(-1.17)
	Equal-weight					
	1d	2d	3d	4d	5d	10d
J:Sorting return horizon						
1d	0.0007	-0.0013	-0.0016	-0.0017	-0.0036	-0.0027
	(3.16)	(-5.10)	(-5.59)	(-5.46)	(-10.87)	(-6.23)
2d	-0.0013	-0.0033	-0.0039	-0.0058	-0.0076	-0.0064
	(-6.97)	(-11.31)	(-10.91)	(-13.93)	(-16.10)	(-10.13)
3d	-0.0015	-0.0034	-0.0054	-0.0074	-0.0088	-0.0074
	(-8.44)	(-11.39)	(-13.21)	(-15.19)	(-15.79)	(-9.66)
5d	-0.0025	-0.0054	-0.0072	-0.0085	-0.0093	-0.0084
	(-13.69)	(-16.10)	(-15.24)	(-15.00)	(-14.39)	(-8.65)
10d	-0.0017	-0.0034	-0.0044	-0.0053	-0.0059	-0.0063
	(-10.04)	(-10.47)	(-9.42)	(-8.81)	(-8.10)	(-4.69)

Table V. New Investors

Panel A reports the means of the age and the male-to-female ratio for the new investor group and the whole retail investor group, respectively. Panel B reports the turnover rates of different investor groups in 2019. *New* refers to investors with less than 3-month trading experience and account value smaller than 3 million RMB; *Gen* refers to investors with more than 3-month trading experience and account value smaller than 3 million RMB; *L* refers to investors with account value greater than 3 million RMB; and *ML* and *OI* refer to mutual funds and other institutions, respectively.

Panel A: Age and Gender

	Age		Male Ratio	
Year	New	All Retail	New	All Retail
2005	36.26	44.28	0.57	0.55
2006	36.18	44.89	0.52	0.54
2007	34.82	42.29	0.53	0.54
2008	33.82	42.31	0.61	0.54
2009	34.37	42.25	0.55	0.54
2010	33.48	42.35	0.54	0.54
2011	32.86	42.70	0.57	0.55
2012	35.27	43.38	0.57	0.55
2013	36.88	44.12	0.57	0.55
2014	36.31	44.57	0.57	0.55
2015	33.46	42.71	0.59	0.56
2016	33.45	42.05	0.56	0.56
2017	34.53	42.07	0.56	0.56
2018	35.31	42.39	0.56	0.56
2019	36.50	42.79	0.57	0.56

Panel B: Turnover

Investor Group	New	Gen	L	MF	OI
Turnover	18.12%	8.03%	3.26%	1.98%	1.66%

Table VI. Cross-Sectional Stock Return Predictability

This table reports the results in the Fama-MacBeth regressions of the future 1-month stock returns on the *Netbuy* of different investor groups. t-statistics are reported in parentheses.

	Ret_{m+1}				
	(1)	(2)	(3)	(4)	(5)
$Netbuy(New)_m$	-0.00347				
	(-5.80)				
$Netbuy(Gen)_m$		-0.00032			
		(-10.75)			
$Netbuy(L)_m$			0.00038		
			(6.85)		
$Netbuy(MF)_m$				0.00021	
				(4.58)	
$Netbuy(OI)_m$					0.00018
					(6.04)
Ln_cap	-0.00492	-0.00292	-0.00318	-0.00324	-0.00320
	(-2.55)	(-1.58)	(-1.68)	(-1.73)	(-1.68)
Abn_turnover	-0.00648	-0.00587	-0.00958	-0.00902	-0.00957
	(-2.97)	(-2.73)	(-4.13)	(-4.17)	(-4.04)
BM	0.01139	0.01165	0.01180	0.01162	0.01182
	(2.76)	(2.96)	(2.74)	(2.79)	(2.90)
Ret_m	-0.02770	-0.07280	-0.03858	-0.03838	-0.03419
	(-2.90)	(-8.32)	(-4.26)	(-4.17)	(-3.75)
$Ret_{m-11\rightarrow m-1}$	0.00051	0.00036	0.00069	-0.00039	-0.00009
	(0.14)	(0.10)	(0.18)	(-0.10)	(-0.02)
Vol	0.31170	0.17766	0.17362	0.12347	0.15217
	(2.52)	(1.42)	(1.34)	(0.99)	(1.23)
Max	-0.12347	-0.11530	-0.12074	-0.11863	-0.11958
	(-4.44)	(-3.96)	(-4.23)	(-4.27)	(-4.23)
Illiq	0.39042	0.63368	0.57492	0.57012	0.57078
	(1.81)	(2.88)	(2.69)	(2.64)	(2.54)
N	108303	108303	108303	108303	108303
R-sq	0.12	0.12	0.12	0.11	0.11

Table VII. Investor Reactions to Daily Returns

This table presents the results in the Fama-MacBeth regressions of the future 1-day *Netbuy* of different investor groups on the stock returns on Day 0, over previous five days, from Days -21 to -6. Hit^U and Hit^D in Panel B are dummy variables indicating whether the stock hits the upper or lower limits on Day 0. t-statistics are reported in parentheses.

Panel A

	$Netbuy(New)_{d+1}$	$Netbuy(Gen)_{d+1}$	$Netbuy(L)_{d+1}$	$Netbuy(MF)_{d+1}$	$Netbuy(OI)_{d+1}$
	(1)	(2)	(3)	(4)	(5)
Ret_d	2.71965	-1.73815	-14.06921	11.56274	-0.29133
	(10.03)	(-1.39)	(-23.94)	(20.03)	(-0.52)
$Ret_{d-5\to d-1}$	0.11478	-5.69894	0.23111	3.51895	0.99036
	(2.67)	(-16.02)	(1.74)	(16.67)	(8.57)
$Ret_{d-21\to d-6}$	-0.00569	-0.80944	-0.27761	0.86031	0.06882
	(-0.45)	(-6.71)	(-5.72)	(10.85)	(1.36)
Ln_cap	-0.00192	0.19981	-0.12065	-0.02390	-0.02929
	(-1.21)	(12.92)	(-14.86)	(-2.68)	(-3.58)
Turnover_float	2.49324	16.15772	-9.94324	-3.58896	-3.41504
	(11.47)	(26.81)	(-26.51)	(-9.61)	(-11.99)
BM	-0.00043	-0.03193	0.07926	-0.02798	-0.00338
	(-0.05)	(-0.68)	(2.99)	(-1.06)	(-0.16)
Constant	0.02559	-3.50405	2.17375	0.37578	0.49584
	(0.85)	(-14.20)	(15.22)	(2.99)	(3.98)
N	2402764	2402764	2402764	2402764	2402764
R-sq	0.079	0.064	0.063	0.052	0.037

Panel B

	$Netbuy(New)_{d+1}$	$Netbuy(Gen)_{d+1}$	$Netbuy(L)_{d+1}$	$Netbuy(MF)_{d+1}$	$Netbuy(OI)_{d+1}$
	(1)	(2)	(3)	(4)	(5)
Ret_d	1.47027	-11.63046	-6.61698	13.12257	1.44521
	(8.66)	(-10.20)	(-16.58)	(21.62)	(2.65)
$Ret_{d-5\rightarrow d-1}$	0.03389	-6.32455	0.63144	3.66452	1.13448
	(0.97)	(-17.96)	(4.86)	(16.95)	(9.83)
$Ret_{d-21\rightarrow d-6}$	-0.01619	-0.85405	-0.25605	0.87830	0.08162
	(-1.38)	(-7.35)	(-5.34)	(11.18)	(1.63)
Ln_cap	-0.00070	0.20023	-0.12031	-0.02654	-0.02869
	(-0.45)	(13.56)	(-15.27)	(-3.02)	(-3.48)
Turnover_float	2.34964	14.29267	-8.55519	-3.41016	-3.12588
	(10.54)	(24.91)	(-22.47)	(-9.56)	(-10.79)
BM	0.01942	0.01840	0.03803	-0.04385	-0.01226
	(2.27)	(0.43)	(1.60)	(-1.69)	(-0.63)
Hit^U	0.50753	4.83179	-3.49746	-0.73436	-0.85658
	(17.90)	(26.41)	(-28.13)	(-18.56)	(-14.50)
Hit^D	0.00982	0.16226	0.06097	0.07610	-0.17090
	(1.25)	(2.03)	(1.32)	(2.80)	(-3.99)
Constant	0.01464	-3.44972	2.12599	0.40807	0.47093
	(0.49)	(-14.70)	(15.38)	(3.31)	(3.79)
N	2402764	2402764	2402764	2402764	2402764
R-sq	0.103	0.091	0.088	0.058	0.046

Table VIII. Price Responses to Past Returns and Investor Trading

This table presents the results in the Fama-MacBeth regressions of the future stock returns over 1-day, Days 2 to 6, and Day 2 to 21, respectively on the future 1-day *Netbuy* of different investor groups and its interaction with the daily return on Day 0. Hit^U and Hit^D are dummy variables indicating whether the stock hits the upper or lower limits on Day 0. t-statistics are reported in parentheses.

Panel A

	Ret_{d+1}	$Ret_{d+2\to d+6}$	$Ret_{d+2\to d+11}$	Ret_{d+1}	$Ret_{d+2\to d+6}$	$Ret_{d+2\to d+11}$
	(1)	(2)	(3)	(4)	(5)	(6)
Ret_d	0.02760	-0.03760	-0.00023	-0.00625	-0.05191	-0.01086
	(6.05)	(-6.10)	(-0.03)	(-1.66)	(-8.76)	(-1.28)
$Ret_{d-5\to d-1}$	-0.01601	-0.01486	-0.00692	-0.01783	-0.01618	-0.00748
	(-14.67)	(-3.77)	(-1.02)	(-16.92)	(-4.22)	(-1.13)
$Ret_{d-21\to d-6}$	-0.00085	-0.00807	-0.01737	-0.00098	-0.00794	-0.01724
	(-1.54)	(-3.10)	(-3.82)	(-1.79)	(-3.05)	(-3.79)
Ln_cap	-0.00051	-0.00180	-0.00317	-0.00050	-0.00179	-0.00315
	(-5.48)	(-3.98)	(-3.76)	(-5.35)	(-3.96)	(-3.73)
Turnover_float	-0.04427	-0.13587	-0.23637	-0.04087	-0.13486	-0.23649
	(-14.84)	(-12.88)	(-13.12)	(-13.86)	(-12.59)	(-12.95)
BM	0.00027	0.00154	0.00251	0.00033	0.00135	0.00226
	(1.14)	(1.32)	(1.15)	(1.30)	(1.16)	(1.03)
$Netbuy(New)_{d+1}$	-0.00718	-0.00226	-0.00272	-0.00712	-0.00215	-0.00288
	(-12.57)	(-8.20)	(-7.81)	(-12.39)	(-7.89)	(-7.72)
$Ret_d * Netbuy(New)_{d+1}$	0.13504	-0.03950	-0.07682	0.08655	-0.03184	-0.04544
	(17.35)	(-5.51)	(-8.36)	(14.35)	(-4.21)	(-4.95)
$Hit^U * Netbuy(New)_{d+1}$				-0.00034	-0.00234	0.00231
				(-0.17)	(-0.75)	(0.48)
$Hit^D * Netbuy(New)_{d+1}$				0.00068	-0.03682	0.00309
				(0.16)	(-1.16)	(0.07)
Hit^U				0.01192	0.00579	-0.00309
				(9.09)	(2.60)	(-0.68)
Hit^D				-0.00816	-0.00096	-0.00249
				(-9.36)	(-0.17)	(-0.38)
Constant	0.00937	0.03084	0.05562	0.00927	0.03086	0.05555
	(5.89)	(4.02)	(3.89)	(5.79)	(4.03)	(3.89)
N	2402764	2402764	2402764	2402764	2402764	2402764
R-sq	0.126	0.102	0.108	0.149	0.113	0.118

Panel B

	Ret_{d+1}	$Ret_{d+2\rightarrow d+6}$	$Ret_{d+2\rightarrow d+11}$	Ret_{d+1}	$Ret_{d+2\rightarrow d+6}$	$Ret_{d+2\rightarrow d+11}$
	(1)	(2)	(3)	(4)	(5)	(6)
Ret_d	0.03274	-0.05185	-0.02265	-0.02660	-0.06615	-0.02871
	(6.77)	(-8.49)	(-2.89)	(-7.21)	(-11.18)	(-3.63)
$Ret_{d-5\rightarrow d-1}$	-0.02744	-0.01862	-0.01214	-0.03138	-0.01984	-0.01249
	(-20.98)	(-4.84)	(-1.84)	(-25.45)	(-5.32)	(-1.94)
$Ret_{d-21\rightarrow d-6}$	-0.00246	-0.00849	-0.01805	-0.00278	-0.00849	-0.01795
	(-4.59)	(-3.28)	(-4.00)	(-5.26)	(-3.28)	(-3.98)
Ln_cap	-0.00001	-0.00172	-0.00308	-0.00001	-0.00175	-0.00310
	(-0.11)	(-3.85)	(-3.66)	(-0.12)	(-3.91)	(-3.69)
Turnover_float	-0.01478	-0.13144	-0.23363	-0.01725	-0.13188	-0.23492
	(-4.93)	(-12.44)	(-13.00)	(-5.82)	(-12.16)	(-12.81)
BM	0.00032	0.00157	0.00260	0.00044	0.00140	0.00236
	(1.49)	(1.36)	(1.19)	(1.91)	(1.22)	(1.08)
$Netbuy(Gen)_{d+1}$	-0.00248	-0.00067	-0.00083	-0.00249	-0.00068	-0.00083
	(-43.67)	(-14.60)	(-14.53)	(-42.83)	(-13.20)	(-13.18)
$Ret_d * Netbuy(Gen)_{d+1}$	0.01028	-0.00451	-0.00556	0.00390	-0.00698	-0.00872
	(17.87)	(-6.04)	(-5.95)	(7.23)	(-8.41)	(-8.16)
$Hit^U * Netbuy(Gen)_{d+1}$				0.00117	0.00028	0.00230
				(1.32)	(0.27)	(1.15)
$Hit^D * Netbuy(Gen)_{d+1}$				-0.00301	0.01583	0.00170
				(-1.32)	(1.26)	(0.15)
Hit^U				0.01438	0.00930	-0.00458
				(3.07)	(1.76)	(-0.55)
Hit^D				-0.00651	-0.00611	0.00284
				(-4.37)	(-0.88)	(0.30)
Constant	0.00022	0.02948	0.05398	0.00051	0.03008	0.05445
	(0.16)	(3.86)	(3.78)	(0.37)	(3.94)	(3.82)
N	2402764	2402764	2402764	2402764	2402764	2402764
R-sq	0.252	0.105	0.111	0.282	0.117	0.121

Panel C

	Ret_{d+1}	$Ret_{d+2\to d+6}$	$Ret_{d+2\to d+11}$	Ret_{d+1}	$Ret_{d+2\to d+6}$	$Ret_{d+2\to d+11}$
	(1)	(2)	(3)	(4)	(5)	(6)
Ret_d	0.05646	-0.04544	-0.01384	0.00585	-0.05617	-0.01442
	(13.16)	(-7.69)	(-1.70)	(1.71)	(-9.65)	(-1.72)
$Ret_{d-5\to d-1}$	-0.01511	-0.01585	-0.00813	-0.01839	-0.01672	-0.00797
	(-13.91)	(-4.01)	(-1.20)	(-17.94)	(-4.36)	(-1.20)
$Ret_{d-21\to d-6}$	-0.00012	-0.00784	-0.01726	-0.00032	-0.00765	-0.01701
	(-0.23)	(-3.02)	(-3.81)	(-0.59)	(-2.95)	(-3.76)
Ln_cap	-0.00034	-0.00175	-0.00311	-0.00033	-0.00177	-0.00312
	(-3.85)	(-3.89)	(-3.69)	(-3.66)	(-3.95)	(-3.71)
Turnover_float	-0.03896	-0.13704	-0.24010	-0.03892	-0.13628	-0.24045
	(-14.00)	(-12.83)	(-13.24)	(-14.06)	(-12.55)	(-13.08)
BM	0.00016	0.00136	0.00238	0.00023	0.00120	0.00215
	(0.67)	(1.16)	(1.08)	(0.90)	(1.02)	(0.98)
$Netbuy(L)_{d+1}$	0.00168	0.00049	0.00064	0.00163	0.00047	0.00061
	(36.23)	(10.99)	(9.57)	(34.58)	(8.94)	(8.84)
$Ret_d * Netbuy(L)_{d+1}$	-0.00670	0.00479	0.00717	-0.00205	0.00578	0.00877
	(-9.62)	(3.24)	(4.50)	(-2.29)	(4.02)	(4.80)
$Hit^U * Netbuy(L)_{d+1}$				0.00160	0.00309	0.00105
				(1.01)	(0.94)	(0.25)
$Hit^D * Netbuy(L)_{d+1}$				-0.00044	0.00323	0.01416
				(-0.25)	(0.56)	(1.12)
Hit^U				0.02251	0.04285	0.02714
				(3.29)	(1.27)	(0.73)
Hit^D				-0.00706	-0.00978	-0.00759
				(-3.75)	(-2.59)	(-1.30)
Constant	0.00583	0.03011	0.05469	0.00583	0.03051	0.05495
	(3.95)	(3.93)	(3.83)	(3.91)	(4.01)	(3.85)
N	2402764	2402764	2402764	2402764	2402764	2402764
R-sq	0.153	0.103	0.100	0.181	0.115	0.119

Panel D

	Ret_{d+1}	$Ret_{d+2\to d+6}$	$Ret_{d+2\to d+11}$	Ret_{d+1}	$Ret_{d+2\to d+6}$	$Ret_{d+2\to d+11}$
	(1)	(2)	(3)	(4)	(5)	(6)
Ret_d	0.02165	-0.06135	-0.03481	-0.02934	-0.06906	-0.03225
	(5.19)	(-10.48)	(-4.49)	(-8.14)	(-11.99)	(-3.99)
$Ret_{d-5\to d-1}$	-0.02236	-0.01761	-0.01084	-0.02534	-0.01810	-0.01009
	(-18.70)	(-4.47)	(-1.62)	(-22.06)	(-4.72)	(-1.54)
$Ret_{d-21\to d-6}$	-0.00252	-0.00871	-0.01821	-0.00279	-0.00857	-0.01796
	(-4.73)	(-3.38)	(-4.05)	(-5.30)	(-3.33)	(-4.01)
Ln_cap	-0.00044	-0.00184	-0.00322	-0.00045	-0.00186	-0.00323
	(-4.79)	(-4.07)	(-3.82)	(-4.85)	(-4.15)	(-3.84)
Turnover_float	-0.03861	-0.14135	-0.24574	-0.04038	-0.14058	-0.24438
	(-14.47)	(-13.39)	(-13.63)	(-15.05)	(-13.09)	(-13.35)
BM	0.00044	0.00155	0.00265	0.00049	0.00137	0.00238
	(1.88)	(1.35)	(1.22)	(1.99)	(1.19)	(1.10)
$Netbuy(MF)_{d+1}$	0.00257	0.00082	0.00114	0.00261	0.00084	0.00113
	(26.18)	(9.03)	(7.20)	(25.31)	(9.02)	(6.70)
$Ret_d * Netbuy(MF)_{d+1}$	-0.00949	0.01253	0.01896	-0.00390	0.01321	0.01918
	(-9.22)	(7.27)	(8.11)	(-4.22)	(7.25)	(7.18)
$Hit^U * Netbuy(MF)_{d+1}$				0.06209	-0.14295	-0.52267
				(1.02)	(-0.87)	(-0.93)
$Hit^D * Netbuy(MF)_{d+1}$				0.08053	0.34449	0.11037
				(0.62)	(0.93)	(0.28)
Hit^U				0.01632	-0.00107	-0.00714
				(22.70)	(-0.48)	(-1.98)
Hit^D				-0.00843	-0.00815	-0.00834
				(-11.15)	(-6.19)	(-5.04)
Constant	0.00765	0.03141	0.05644	0.00804	0.03179	0.05646
	(4.87)	(4.09)	(3.94)	(5.07)	(4.16)	(3.96)
N	2402764	2402764	2402764	2402764	2402764	2402764
R-sq	0.142	0.102	0.108	0.167	0.112	0.118

Panel E

	Ret_{d+1}	$Ret_{d+2\rightarrow d+6}$	$Ret_{d+2\rightarrow d+11}$	Ret_{d+1}	$Ret_{d+2\rightarrow d+6}$	$Ret_{d+2\rightarrow d+11}$
	(1)	(2)	(3)	(4)	(5)	(6)
Ret_d	0.04320	-0.05279	-0.02443	-0.00359	-0.06093	-0.02238
	(10.87)	(-8.73)	(-3.02)	(-1.11)	(-10.24)	(-2.69)
$Ret_{d-5\rightarrow d-1}$	-0.01628	-0.01604	-0.00887	-0.01903	-0.01671	-0.00848
	(-14.50)	(-4.05)	(-1.31)	(-17.75)	(-4.36)	(-1.28)
$Ret_{d-21\rightarrow d-6}$	-0.00078	-0.00805	-0.01746	-0.00103	-0.00797	-0.01722
	(-1.43)	(-3.09)	(-3.85)	(-1.89)	(-3.06)	(-3.79)
Ln_cap	-0.00045	-0.00179	-0.00316	-0.00046	-0.00181	-0.00318
	(-4.92)	(-3.95)	(-3.73)	(-4.95)	(-4.00)	(-3.76)
Turnover_float	-0.04263	-0.14060	-0.24451	-0.04349	-0.14019	-0.24458
	(-15.36)	(-13.13)	(-13.46)	(-16.11)	(-12.86)	(-13.27)
BM	0.00043	0.00150	0.00254	0.00045	0.00130	0.00226
	(1.78)	(1.30)	(1.16)	(1.77)	(1.12)	(1.03)
$Netbuy(OI)_{d+1}$	0.00135	0.00043	0.00064	0.00136	0.00043	0.00065
	(24.14)	(6.92)	(7.52)	(23.61)	(6.18)	(7.91)
$Ret_d * Netbuy(OI)_{d+1}$	-0.00882	0.00504	0.00704	-0.00284	0.00521	0.00524
	(-9.66)	(3.28)	(3.17)	(-3.22)	(2.92)	(2.09)
$Hit^U * Netbuy(OI)_{d+1}$				0.00810	-0.00665	-0.01489
				(0.73)	(-0.70)	(-0.95)
$Hit^D * Netbuy(OI)_{d+1}$				0.00467	0.02864	-0.00045
				(0.85)	(1.34)	(-0.04)
Hit^U				0.01284	0.00224	-0.00188
				(10.97)	(1.75)	(-0.87)
Hit^D				-0.00812	0.00442	0.00601
				(-7.85)	(0.42)	(0.49)
Consant	0.00781	0.03087	0.05563	0.00822	0.03126	0.05592
	(5.06)	(4.00)	(3.87)	(5.25)	(4.07)	(3.91)
N	2402764	2402764	2402764	2402764	2402764	2402764
R-sq	0.128	0.101	0.108	0.153	0.113	0.118

Panel F

	Ret_{d+1}	$Ret_{d+2\to d+6}$	$Ret_{d+2\to d+11}$	Ret_{d+1}	$Ret_{d+2\to d+6}$	$Ret_{d+2\to d+11}$
	(1)	(2)	(3)	(4)	(5)	(6)
Ret_d	-0.00489	-0.04531	-0.01049	-0.04503	-0.05962	-0.02460
	(-0.99)	(-6.85)	(-1.31)	(-11.55)	(-9.30)	(-3.00)
$Ret_{d-5\to d-1}$	-0.03002	-0.01785	-0.01071	-0.03296	-0.01880	-0.01098
	(-23.89)	(-4.61)	(-1.63)	(-27.47)	(-4.99)	(-1.71)
$Ret_{d-21\to d-6}$	-0.00281	-0.00845	-0.01769	-0.00293	-0.00829	-0.01748
	(-5.30)	(-3.30)	(-3.96)	(-5.50)	(-3.23)	(-3.90)
Ln_cap	-0.00005	-0.00177	-0.00313	-0.00003	-0.00180	-0.00316
	(-0.57)	(-4.00)	(-3.75)	(-0.32)	(-4.06)	(-3.79)
Turnover_float	-0.02763	-0.13415	-0.23710	-0.02475	-0.13551	-0.24014
	(-9.20)	(-12.63)	(-13.07)	(-8.27)	(-12.48)	(-12.98)
BM	0.00034	0.00159	0.00269	0.00044	0.00145	0.00251
	(1.58)	(1.39)	(1.24)	(2.04)	(1.28)	(1.16)
$Netbuy(New)_{d+1}$	-0.00066	-0.00079	-0.00122	-0.00058	-0.00072	-0.00176
	(-2.30)	(-3.32)	(-3.83)	(-2.05)	(-3.37)	(-2.92)
$Ret_d * Netbuy(New)_{d+1}$	0.16582	-0.01698	-0.04744	0.09163	-0.01449	-0.01315
	(17.50)	(-2.52)	(-5.31)	(15.72)	(-1.93)	(-1.18)
$Hit^U * Netbuy(New)_{d+1}$				-0.02560	-0.03743	-0.06103
				(-1.18)	(-0.88)	(-1.04)
$Hit^D * Netbuy(New)_{d+1}$				0.00299	0.02379	0.03721
				(0.66)	(2.20)	(2.08)
$Netbuy(Gen)_{d+1}$	-0.00211	-0.00062	-0.00077	-0.00215	-0.00062	-0.00079
	(-30.00)	(-9.22)	(-9.82)	(-29.38)	(-8.36)	(-10.03)
$Ret_d * Netbuy(Gen)_{d+1}$	0.00446	-0.00465	-0.00474	0.00243	-0.00579	-0.00667
	(5.17)	(-3.20)	(-2.59)	(2.46)	(-3.20)	(-2.85)
$Hit^U * Netbuy(Gen)_{d+1}$				0.05992	0.00496	0.00257
				(1.20)	(0.15)	(0.05)
$Hit^D * Netbuy(Gen)_{d+1}$				-0.00229	0.00006	0.00190
				(-0.73)	(0.01)	(0.12)
$Netbuy(L)_{d+1}$	0.00043	0.00009	0.00008	0.00039	0.00005	0.00004
	(7.55)	(1.19)	(0.97)	(6.88)	(0.59)	(0.39)
$Ret_d * Netbuy(L)_{d+1}$	-0.00215	0.00046	0.00082	-0.00119	0.00111	0.00283
	(-2.35)	(0.27)	(0.43)	(-0.99)	(0.60)	(1.14)
$Hit^U * Netbuy(L)_{d+1}$				0.05184	0.00805	0.00703
				(1.20)	(0.26)	(0.14)
$Hit^D * Netbuy(L)_{d+1}$				-0.00126	0.00002	0.00034
				(-0.41)	(0.00)	(0.02)
$Netbuy(MF)_{d+1}$	0.00105	0.00030	0.00043	0.00105	0.00028	0.00032
	(14.40)	(3.50)	(2.69)	(14.19)	(2.83)	(1.43)
$Ret_d * Netbuy(MF)_{d+1}$	-0.00095	0.00807	0.01239	0.00009	0.00985	0.01667
	(-0.86)	(3.66)	(4.43)	(0.08)	(3.71)	(3.78)
$Hit^U * Netbuy(MF)_{d+1}$				0.29370	0.02345	-0.35841
				(1.92)	(0.21)	(-0.76)
$Hit^D * Netbuy(MF)_{d+1}$				0.04804	-0.17306	-0.31175
				(1.11)	(-0.88)	(-0.93)
Hit^U				-0.07703	0.07766	0.11010
				(-0.80)	(1.74)	(1.39)
Hit^D				-0.00389	-0.00723	-0.01058
				(-4.57)	(-2.82)	(-2.87)
Constant	0.00109	0.03008	0.05456	0.00085	0.03061	0.05542
	(0.80)	(3.97)	(3.84)	(0.63)	(4.05)	(3.92)
N	2402764	2402764	2402764	2402764	2402764	2402764
R-sq	0.301	0.128	0.132	0.334	0.147	0.149

Table IX. Market Up and Down

This table reports new investor reactions to daily returns, when market returns are above the median ("Market-up") and below the median ("Market-down"). Hit^U and Hit^D are dummy variables indicating whether the stock hits the upper or lower limits on Day 0. t-statistics are reported in parentheses.

Dependent Variable:	$Netbuy(New)_{d+1}$		$Netbuy(New)_{d+1}$	
	Market-up	Market-down	Market-up	Market-down
	(1)	(2)	(3)	(4)
Ret_d	3.64145	1.79886	1.90000	1.04103
	(7.03)	(12.41)	(5.82)	(11.44)
$Ret_{d-5\rightarrow d-1}$	0.24206	-0.01236	0.11833	-0.05046
	(2.79)	(-0.47)	(1.70)	(-1.95)
$Ret_{d-21\rightarrow d-6}$	0.03811	-0.04945	0.01892	-0.05127
	(1.44)	(-4.70)	(0.81)	(-4.93)
Ln_cap	-0.00355	-0.00029	-0.00168	0.00027
	(-1.33)	(-0.20)	(-0.66)	(0.18)
Turnover_float	3.48388	1.50370	3.36911	1.33130
	(8.38)	(9.93)	(7.95)	(9.08)
BM	-0.00001	-0.00085	0.03221	0.00663
	(-0.00)	(-0.16)	(2.12)	(1.26)
Hit^U			0.54899	0.46613
			(11.97)	(15.41)
Hit^D			0.01321	0.00644
			(1.11)	(0.60)
Constant	-0.00064	0.05180	-0.00658	0.03584
	(-0.01)	(2.33)	(-0.13)	(1.46)
N	1170077	1232687	1170077	1232687
R-sq	0.089	0.069	0.115	0.092

Table X. Daily Momentum or Reversal in International Markets

This table presents the daily momentum or reversal in major markets from January 1980 to March 2023 (emerging markets on the left and developed markets on the right) around the world. For each market each day, we sort stocks into quintiles based on return on day d. Then, we calculate the portfolio return on day $d+1$, value-weighted by market capitalization at the most recent month-end or equal weighted. The return of a portfolio that longs the top quintile and shorts the bottom is reported, and Newey-West standard errors with lag of 21 days is used. t-statistics are reported in parentheses. "Exist momentum" in Panel B means the average return is larger than 0. "Significant momentum" means the t-statistics is larger than 1.96.

Panel A

Emerging Markets	Value Weighted	Equal Weighted	Price Limit	Developed Markets	Value Weighted	Equal Weighted	Price Limit
Brazil	-0.0016	-0.0058	No	Austria	0.0020	-0.0001	No
	(-5.86)	(-23.47)			(5.96)	(-0.36)	
Chile	0.0031	0.0042	No	Australia	-0.0034	-0.0211	No
	(12.70)	(17.54)			(-15.40)	(-46.39)	
China	0.0013	0.0011	Yes	Belgium	-0.0019	-0.0042	No
	(6.64)	(5.74)			(-11.49)	(-22.87)	
Czech Republic	0.0156	0.0282	No	Canada	-0.0159	-0.0610	No
	(10.40)	(16.14)			(-18.96)	(-38.97)	
Egypt	0.0079	0.0087	Yes	Denmark	-0.0005	-0.0070	No
	(18.14)	(19.63)			(-2.32)	(-21.24)	
Greece	0.0029	0.0002	No	Finland	-0.0027	-0.0089	No
	(6.44)	(0.28)			(-12.22)	(-37.73)	
India	-0.0001	-0.0048	Yes	France	-0.0005	-0.0032	No
	(-0.11)	(-5.51)			(-3.60)	(-17.01)	
Indonesia	-0.0084	-0.0167	Yes	Germany	-0.0010	-0.0067	No
	(-9.61)	(-17.12)			(-5.49)	(-18.01)	
Israel	0.0060	0.0065	No	Hong Kong	-0.0001	-0.0052	No
	(16.09)	(16.36)			(-0.29)	(-15.40)	
Malaysia	-0.0050	-0.0144	Yes	Italy	-0.0003	-0.0031	No
	(-20.72)	(-24.82)			(-2.00)	(-20.89)	
Mexico	0.0043	0.0047	No	Japan	-0.0017	-0.0041	Yes
	(8.43)	(8.96)			(-11.38)	(-30.72)	
Pakistan	0.0029	-0.0055	Yes	Netherlands	0.0005	-0.0017	No
	(6.27)	(-9.29)			(2.76)	(-9.03)	
Philippines	-0.0049	-0.0122	Yes	New Zealand	-0.0013	-0.0060	No
	(-11.82)	(-32.34)			(-6.04)	(-26.27)	
Poland	-0.0016	-0.0096	Yes	Norway	-0.0024	-0.0070	No
	(-5.72)	(-21.60)			(-10.68)	(-23.36)	
Saudi Arabia	0.0016	0.0013	Yes	Portugal	-0.0021	-0.0048	No
	(6.56)	(7.06)			(-3.00)	(-7.99)	
South Africa	0.0014	-0.0082	No	Singapore	-0.0069	-0.0219	No
	(4.06)	(-14.71)			(-21.54)	(-24.67)	
South Korea	0.0033	0.0025	Yes	Spain	0.0002	-0.0020	No
	(10.69)	(8.23)			(1.36)	(-12.02)	
Taiwan	0.0018	0.0032	Yes	Sweden	-0.0018	-0.0096	No
	(6.76)	(11.03)			(-8.86)	(-29.41)	
Thailand	-0.0009	-0.0056	Yes	Switzerland	-0.0007	-0.0049	No
	(-2.73)	(-12.20)			(-5.04)	(-35.93)	
Turkey	0.0018	0.0007	Yes	UK	0.0020	0.0059	No
	(4.47)	(1.77)			(11.07)	(16.31)	
Vietnam	0.0032	-0.0043	Yes	USA	-0.0005	-0.0168	No
	(4.93)	(-5.84)			(-2.67)	(-30.60)	

Panel B

	Value Weighted	Equal Weighted	Value Weighted	Equal Weighted
	All emerging market		All developed market	
Total number	21	21	21	21
Exist momentum	14	11	3	1
Momentum significant at 5% level	14	10	3	1
	Emerging market without price limit		Developed market without price limit	
Total number	7	7	20	20
Exist momentum	6	5	3	1
Momentum significant at 5% level	6	5	3	1
	Emerging market with price limit		Developed market with price limit	
Total number	14	14	1	1
Exist momentum	8	6	0	0
Momentum significant at 5% level	8	5	0	0

Table XI. Market Up&Down and Daily Momentum in International Markets

This table reports the results in major markets that exhibit daily momentum, when market returns are above the median ("Market-up") and below the median ("Market-down"). Sample period is from January 1980 to March 2023. t-statistics are reported in parentheses. "Up>Down" in Panel B indicates the average return of daily momentum is higher in "Marker-up". We further run a time series regression of daily momentum and "Marker-up". "Up>Down Significantly " means that the t-statistics of "Marker-up" is larger than 1.96.

Panel A

	Value weighted		Equal weighted	
	Market-up	Market-down	Market-up	Market-down
Austria	0.0017	0.0023	-0.0002	-0.0001
	(3.73)	(4.71)	(-0.35)	(-0.18)
Chile	0.0040	0.0022	0.0053	0.0032
	(11.26)	(7.09)	(15.04)	(10.85)
China	0.0017	0.0009	0.0017	0.0004
	(6.12)	(3.30)	(5.89)	(2.03)
Czechrepublic	0.0155	0.0172	0.0262	0.0319
	(9.09)	(8.27)	(12.88)	(13.84)
Egypt	0.0096	0.0062	0.0109	0.0065
	(15.50)	(11.01)	(16.82)	(12.48)
Greece	0.0041	0.0018	0.0020	-0.0017
	(5.68)	(3.39)	(2.21)	(-2.86)
Israel	0.0079	0.0042	0.0082	0.0049
	(13.34)	(10.43)	(13.60)	(10.44)
Mexico	0.0055	0.0032	0.0056	0.0038
	(7.63)	(4.33)	(8.46)	(4.85)
Netherlands	0.0012	-0.0002	-0.0006	-0.0028
	(5.18)	(-0.76)	(-2.26)	(-10.84)
Pakistan	0.0052	0.0006	-0.0036	-0.0075
	(8.55)	(0.88)	(-4.24)	(-9.37)
South Africa	0.0027	0.0001	-0.0062	-0.0102
	(6.12)	(0.11)	(-7.47)	(-14.44)
Saudi Arabia	0.0026	0.0006	0.0018	0.0009
	(7.98)	(1.73)	(6.98)	(3.16)
South Korea	0.0045	0.0022	0.0037	0.0014
	(9.53)	(5.82)	(8.12)	(3.69)
Taiwan	0.0013	0.0023	0.0033	0.0030
	(3.78)	(5.74)	(7.83)	(7.78)
Turkey	0.0036	-0.0001	0.0031	-0.0017
	(5.47)	(-0.22)	(5.16)	(-4.26)
UK	0.0030	0.0010	0.0078	0.0041
	(11.88)	(4.31)	(15.26)	(8.37)
Vietnam	0.0033	0.0024	-0.0038	-0.0057
	(3.90)	(2.80)	(-3.91)	(-6.35)

Panel B

	Value Weighted	Equal Weighted
Total number	17	17
Up>Down	14	15
Up>Down Significantly	13	12

Internet Appendix for "Daily Momentum and New Investors in an Emerging Stock Market"

Zhenyu Gao, Wenxi Jiang, Wei A. Xiong, Wei Xiong

Table A1. Time-series and Cross-sectional Summary Statistics

This table reports the means, standard deviations, and quartiles for variables defined in the Appendix. Panel A reports monthly time-series sample. Panel B reports monthly cross-sectional sample. Panel C reports daily cross-sectional sample.

Panel A: Time-series (monthly)

	Mean	SD	p25	p50	p75	N
Frac_ni	0.0368	0.0351	0.0129	0.0292	0.0442	180
Mkt_ret_{m+1}	0.0437	0.1785	-0.0537	0.0056	0.1405	177
Mkt_ret_{m+6}	0.1027	0.3237	-0.0911	0.0365	0.2054	174
Mkt_ret_{m+12}	0.2451	0.6164	-0.1006	0.0693	0.3158	168
Mkt_ret_{m}	0.0131	0.0856	-0.0313	0.0144	0.0518	180
Mkt_ret_{m-6}	0.1015	0.3242	-0.0937	0.0351	0.2054	174
Mkt_vol	0.4005	0.1512	0.2932	0.3521	0.4839	180
Mkt_turnover	8.7431	17.8099	2.5633	3.4064	5.7994	180
BM	0.5959	0.1823	0.4659	0.6388	0.7313	180

Panel B: Cross-sectional (monthly)

	Mean	SD	p25	p50	p75	N
$Netbuy(Retail)_m$	0.71226	29.49750	-6.25175	0.43529	9.05737	108303
$Netbuy(New)_m$	2.20677	5.00163	0.23440	0.82599	2.28193	108303
$Netbuy(Gen)_m$	-1.84592	30.58776	-10.47359	-0.44758	8.80716	108303
$Netbuy(L)_m$	-0.53676	16.49085	-5.87130	-0.27499	5.10981	108303
$Netbuy(MF)_m$	0.66608	21.99944	-3.03466	0.00000	2.07105	108303
$Netbuy(OI)_m$	-1.31534	17.53537	-6.04047	-0.29852	4.12218	108303
Ret_{m+1}	0.01257	0.14058	-0.07042	0.00282	0.08407	108303
Ret_{m+3}	0.04419	0.26852	-0.12106	0.00088	0.15898	108303
Ret_{m+6}	0.09749	0.42067	-0.16354	0.01204	0.25199	108303
Ret_{m+12}	0.22908	0.73965	-0.21945	0.04087	0.44420	108303
Ret_dgtw_{m+1}	-0.00067	0.09445	-0.05490	-0.01026	0.04055	108303
Ret_dgtw_{m+3}	-0.00253	0.16157	-0.09968	-0.02585	0.06693	108303
Ret_dgtw_{m+6}	-0.00432	0.23350	-0.14875	-0.04313	0.09197	108303
Ret_dgtw_{m+12}	-0.00339	0.34646	-0.22051	-0.07179	0.13034	108303
Ln_cap	14.87940	1.15312	14.11846	14.88120	15.61916	108303
EP	0.01528	0.04206	0.00398	0.01257	0.02612	108303
BM	0.39162	0.25543	0.20885	0.33183	0.51117	108303
Vol	0.02798	0.01214	0.01918	0.02556	0.03433	108303
Max	0.05508	0.02748	0.03308	0.04892	0.07509	108303
Turnover_float	0.02647	0.01856	0.01249	0.02176	0.03577	108303
Abn_tnr_float	0.98093	0.59687	0.54736	0.83080	1.25955	108303
Ret_m	0.01213	0.14106	-0.07119	0.00230	0.08391	108303
Illiq	0.00875	0.01700	0.00205	0.00438	0.00952	108303

Panel C: Cross-sectional (daily)

	Mean	SD	p25	p50	p75	N
Ret_{d+1}	0.00062	0.02919	-0.01379	0.00063	0.01465	2418806
$Netbuy(New)_d$	0.07205	0.50629	-0.05025	0.01914	0.13278	2418806
$Netbuy(OI)_d$	-0.02217	2.42562	-0.54361	0.00000	0.54585	2418806
$Netbuy(MF)_d$	0.01613	1.97471	-0.03851	0.00000	0.03337	2418806
$Netbuy(L)_d$	-0.01954	3.04808	-0.78896	0.00530	0.79336	2418806
$Netbuy(Gen)_d$	-0.09226	3.88551	-1.14557	-0.06121	0.98618	2418806
Ln_cap	15.03913	1.10968	14.34351	15.05439	15.73465	2418806
Turnover_float	0.02375	0.02666	0.00727	0.01450	0.02955	2418806
BM	0.40681	0.29382	0.20186	0.33759	0.53710	2418806

Table A2. Time Series Analysis

This table reports results in the time-series Newey-West regressions (with lags of 11 months) of the future 1-month, 3-month, 6-month, and 12-month market returns on the fraction of new investors. t-statistics are reported in parentheses.

	Mkt_ret_{m+1}	Mkt_ret_{m+3}	Mkt_ret_{m+6}	Mkt_ret_{m+12}
	(1)	(2)	(3)	(4)
Frac_ni	-0.5289	-2.39608	-6.6792	-15.80738
	(-1.48)	(-2.20)	(-2.70)	(-2.82)
Mkt_vol	0.03633	0.35082	0.73012	1.77305
	(0.87)	(2.48)	(3.02)	(4.04)
Mkt_turnover	-0.00008	-0.00058	-0.00121	-0.00144
	(-0.42)	(-1.22)	(-1.33)	(-0.85)
Mkt_BM	0.04942	0.19951	0.22204	0.30962
	(0.86)	(1.19)	(0.770	(0.69)
Mkt_ret_m	0.14782	0.43617	0.85764	1.02343
	(2.3)	(2.49)	(3.01)	(2.52)
Mkt_ret_{m-12}	0.03414	0.10962	0.21454	0.37635
	(1.25)	(1.44)	(1.43)	(1.65)
Constant	-0.01968	-0.15201	-0.12471	-0.15404
	(-0.50)	(-1.33)	(-0.54)	(-0.38)
N	180	180	180	180
R-sq	0.048	0.151	0.272	0.393

Table A3. Cross-sectional Predictions

This table reports the results in the Fama-MacBeth regressions of the future 3 (Panel A), 6 (Panel B), 12 (Panel C)-month stock returns as well as the future 1 (Panel D), 3 (Panel E), 6 (Panel F), 12 (Panel G)-month DGTW stock returns on the *Netbuy* of different investor groups. t-statistics are reported in parentheses.

Panel A:			Ret_{m+3}		
	(1)	(2)	(3)	(4)	(5)
$Netbuy(New)_m$	-0.00543				
	(-5.46)				
$Netbuy(Gen)_m$		-0.00049			
		(-11.56)			
$Netbuy(L)_m$			0.00063		
			(5.26)		
$Netbuy(MF)_m$				0.00034	
				(5.28)	
$Netbuy(OI)_m$					0.00027
					(3.66)
Ln_cap	-0.01177	-0.00876	-0.00901	-0.00897	-0.00908
	(-2.24)	(-1.69)	(-1.71)	(-1.71)	(-1.72)
Abn_turnover	-0.00756	-0.00694	-0.01253	-0.01149	-0.01265
	(-2.01)	(-1.83)	(-3.01)	(-3.05)	(-3.08)
BM	0.02450	0.02529	0.02467	0.02566	0.02505
	(1.94)	(2.08)	(2.00)	(2.07)	(2.02)
Ret_m	-0.02197	-0.09112	-0.03941	-0.03924	-0.03057
	(-0.99)	(-4.36)	(-1.82)	(-1.84)	(-1.46)
$Ret_{m-11\rightarrow m-1}$	-0.00093	-0.00169	-0.00111	-0.00284	-0.00230
	(-0.08)	(-0.15)	(-0.10)	(-0.25)	(-0.21)
Vol	-0.01381	-0.20396	-0.19901	-0.25828	-0.25315
	(-0.05)	(-0.75)	(-0.72)	(-0.96)	(-0.95)
Max	-0.16805	-0.15540	-0.16677	-0.16835	-0.15461
	(-3.62)	(-3.32)	(-3.62)	(-3.51)	(-3.21)
Illiq	1.14474	1.51200	1.45492	1.43043	1.43146
	(2.17)	(2.69)	(2.66)	(2.62)	(2.53)
N	108303	108303	108303	108303	108303
R-sq	0.11	0.12	0.11	0.11	0.11

Panel B:	Ret_{m+6}				
	(1)	(2)	(3)	(4)	(5)
$Netbuy(New)_m$	-0.00823				
	(-6.13)				
$Netbuy(Gen)_m$		-0.00069			
		(-9.36)			
$Netbuy(L)_m$			0.00092		
			(4.17)		
$Netbuy(MF)_m$				0.00048	
				(4.31)	
$Netbuy(OI)_m$					0.00040
					(3.38)
Ln_cap	-0.02182	-0.01760	-0.01798	-0.01802	-0.01794
	(-2.39)	(-1.92)	(-1.94)	(-1.96)	(-1.94)
Abn_turnover	-0.01027	-0.01021	-0.01777	-0.01671	-0.01797
	(-1.39)	(-1.41)	(-2.39)	(-2.28)	(-2.42)
BM	0.04186	0.04288	0.04227	0.04389	0.04296
	(1.85)	(1.93)	(1.90)	(1.94)	(1.93)
Ret_m	0.00310	-0.09175	-0.02001	-0.01862	-0.00820
	(0.09)	(-2.86)	(-0.61)	(-0.57)	(-0.26)
$Ret_{m-11\rightarrow m-1}$	-0.01378	-0.01419	-0.01400	-0.01589	-0.01513
	(-0.55)	(-0.56)	(-0.56)	(-0.63)	(-0.60)
Vol	-0.60653	-0.86539	-0.87207	-0.95320	-0.92625
	(-1.34)	(-1.94)	(-1.83)	(-2.04)	(-2.02)
Max	-0.19185	-0.18708	-0.19203	-0.19435	-0.18469
	(-2.00)	(-1.95)	(-1.88)	(-1.88)	(-1.84)
Illiq	1.76597	2.27426	2.20687	2.17701	2.15839
	(1.78)	(2.20)	(2.17)	(2.17)	(2.09)
N	108303	108303	108303	108303	108303
R-sq	0.10	0.10	0.10	0.10	0.10

Panel C:			Ret_{m+12}		
	(1)	(2)	(3)	(4)	(5)
$Netbuy(New)_m$	-0.01073				
	(-5.11)				
$Netbuy(Gen)_m$		-0.00096			
		(-5.60)			
$Netbuy(L)_m$			0.00166		
			(2.82)		
$Netbuy(MF)_m$				0.00068	
				(3.27)	
$Netbuy(OI)_m$					0.00066
					(2.47)
Ln_cap	-0.03824	-0.03323	-0.03326	-0.03362	-0.03408
	(-1.84)	(-1.63)	(-1.61)	(-1.64)	(-1.65)
Abn_turnover	-0.00172	-0.00208	-0.01090	-0.00948	-0.01064
	(-0.20)	(-0.23)	(-1.30)	(-1.05)	(-1.22)
BM	0.07369	0.07663	0.07505	0.07658	0.07597
	(1.78)	(1.84)	(1.80)	(1.84)	(1.82)
Ret_m	-0.00407	-0.13380	-0.04639	-0.04426	-0.02684
	(-0.08)	(-2.88)	(-0.99)	(-0.99)	(-0.58)
$Ret_{m-11\rightarrow m-1}$	-0.02622	-0.02610	-0.02671	-0.02889	-0.02811
	(-0.70)	(-0.68)	(-0.71)	(-0.77)	(-0.75)
Vol	-2.82164	-3.17009	-3.21230	-3.34010	-3.25914
	(-4.69)	(-5.54)	(-5.52)	(-5.92)	(-5.57)
Max	0.11434	0.13901	0.13128	0.14606	0.13276
	(0.74)	(0.93)	(0.85)	(0.93)	(0.86)
Illiq	3.88349	4.50690	4.49155	4.44640	4.37934
	(2.76)	(3.08)	(3.15)	(3.13)	(3.03)
N	108303	108303	108303	108303	108303
R-sq	0.10	0.10	0.10	0.10	0.10

Panel D:	Ret_dgtw_{m+1}				
	(1)	(2)	(3)	(4)	(5)
$Netbuy(New)_m$	-0.00306				
	(-5.39)				
$Netbuy(Gen)_m$		-0.00028			
		(-10.43)			
$Netbuy(L)_m$			0.00034		
			(7.04)		
$Netbuy(MF)_m$				0.00018	
				(4.15)	
$Netbuy(OI)_m$					0.00015
					(5.96)
Ln_cap	0.00003	0.00176	0.00152	0.00150	0.00151
	(0.05)	(2.79)	(2.26)	(2.39)	(2.21)
Abn_turnover	-0.00579	-0.00521	-0.00846	-0.00802	-0.00849
	(-2.99)	(-2.81)	(-4.28)	(-4.41)	(-4.17)
BM	0.00007	0.00012	0.00026	0.00021	0.00040
	(0.03)	(0.07)	(0.12)	(0.11)	(0.20)
Ret_m	-0.02188	-0.06133	-0.03196	-0.03083	-0.02771
	(-3.56)	(-10.50)	(-5.48)	(-5.04)	(-4.61)
$Ret_{m-11\rightarrow m-1}$	0.00390	0.00379	0.00409	0.00316	0.00338
	(3.57)	(3.98)	(3.83)	(3.18)	(3.27)
Vol	0.26546	0.15142	0.14964	0.10398	0.12676
	(2.46)	(1.38)	(1.33)	(0.98)	(1.20)
Max	-0.10593	-0.09882	-0.10291	-0.10138	-0.10205
	(-4.31)	(-3.87)	(-4.16)	(-4.21)	(-4.18)
Illiq	0.33567	0.54775	0.49380	0.49356	0.49438
	(1.79)	(2.85)	(2.67)	(2.63)	(2.51)
N	108303	108303	108303	108303	108303
R-sq	0.05	0.05	0.05	0.05	0.05

Panel E:	Ret_dgtw_{m+3}				
	(1)	(2)	(3)	(4)	(5)
$Netbuy(New)_m$	-0.00497				
	(-4.75)				
$Netbuy(Gen)_m$		-0.00044			
		(-9.62)			
$Netbuy(L)_m$			0.00056		
			(5.93)		
$Netbuy(MF)_m$				0.00032	
				(4.56)	
$Netbuy(OI)_m$					0.00021
					(3.85)
Ln_cap	0.00297	0.00563	0.00536	0.00540	0.00537
	(2.06)	(3.45)	(3.23)	(3.46)	(3.16)
Abn_turnover	-0.00611	-0.00547	-0.01061	-0.00943	-0.01071
	(-2.00)	(-2.01)	(-3.46)	(-3.55)	(-3.52)
BM	-0.01094	-0.01039	-0.01087	-0.01003	-0.01057
	(-1.83)	(-1.76)	(-1.83)	(-1.75)	(-1.76)
Ret_m	-0.00852	-0.06947	-0.02446	-0.02463	-0.01560
	(-0.68)	(-5.92)	(-1.95)	(-2.03)	(-1.27)
$Ret_{m-11\to m-1}$	0.00714	0.00644	0.00709	0.00552	0.00597
	(3.06)	(3.00)	(3.16)	(2.51)	(2.72)
Vol	0.16200	-0.00508	-0.00393	-0.05376	-0.05103
	(0.69)	(-0.02)	(-0.02)	(-0.23)	(-0.22)
Max	-0.15038	-0.13891	-0.14841	-0.15083	-0.14073
	(-3.37)	(-3.15)	(-3.38)	(-3.32)	(-3.10)
Illiq	1.05016	1.39247	1.32477	1.30908	1.32351
	(2.32)	(2.83)	(2.80)	(2.77)	(2.64)
N	108303	108303	108303	108303	108303
R-sq	0.05	0.05	0.04	0.04	0.04

Panel F:	Ret_dgtw_{m+6}				
	(1)	(2)	(3)	(4)	(5)
$Netbuy(New)_m$	-0.00754				
	(-5.39)				
$Netbuy(Gen)_m$		-0.00061			
		(-8.81)			
$Netbuy(L)_m$			0.00075		
			(5.00)		
$Netbuy(MF)_m$				0.00046	
				(4.09)	
$Netbuy(OI)_m$					0.00029
					(3.79)
Ln_cap	0.00555	0.00936	0.00901	0.00902	0.00904
	(2.36)	(3.53)	(3.40)	(3.59)	(3.34)
Abn_turnover	-0.00575	-0.00562	-0.01276	-0.01116	-0.01287
	(-1.04)	(-1.10)	(-2.51)	(-2.28)	(-2.51)
BM	-0.02956	-0.02873	-0.02935	-0.02812	-0.02890
	(-2.61)	(-2.50)	(-2.56)	(-2.53)	(-2.50)
Ret_m	0.01906	-0.06287	-0.00132	-0.00341	0.00896
	(1.32)	(-4.41)	(-0.09)	(-0.23)	(0.65)
$Ret_{m-11\rightarrow m-1}$	0.00011	-0.00067	-0.00019	-0.00194	-0.00135
	(0.02)	(-0.12)	(-0.04)	(-0.36)	(-0.26)
Vol	-0.20250	-0.44561	-0.45545	-0.52239	-0.50325
	(-0.52)	(-1.13)	(-1.09)	(-1.29)	(-1.25)
Max	-0.14514	-0.13364	-0.13944	-0.14181	-0.1346
	(-1.89)	(-1.72)	(-1.75)	(-1.76)	(-1.68)
Illiq	1.72867	2.19834	2.11896	2.08749	2.10158
	(2.15)	(2.55)	(2.53)	(2.52)	(2.43)
N	108303	108303	108303	108303	108303
R-sq	0.04	0.04	0.04	0.04	0.04

Panel G:	Ret_dgtw_{m+12}				
	(1)	(2)	(3)	(4)	(5)
$Netbuy(New)_m$	-0.00929				
	(-5.13)				
$Netbuy(Gen)_m$		-0.00079			
		(-8.50)			
$Netbuy(L)_m$			0.00110		
			(4.01)		
$Netbuy(MF)_m$				0.00062	
				(3.77)	
$Netbuy(OI)_m$					0.00036
					(3.19)
Ln_cap	0.01154	0.01665	0.01622	0.01598	0.01596
	(2.35)	(3.21)	(3.13)	(3.20)	(3.07)
Abn_turnover	0.00116	0.00045	-0.00865	-0.00559	-0.00853
	(0.16)	(0.06)	(-1.29)	(-0.78)	(-1.21)
BM	-0.06663	-0.06513	-0.06651	-0.06471	-0.06562
	(-3.34)	(-3.24)	(-3.30)	(-3.31)	(-3.27)
Ret_m	0.03404	-0.07168	0.00686	-0.00020	0.02124
	(2.01)	(-3.90)	(0.42)	(-0.01)	(1.25)
$Ret_{m-11\rightarrow m-1}$	-0.01813	-0.01891	-0.01847	-0.02097	-0.02011
	(-1.82)	(-1.80)	(-1.80)	(-2.01)	(-1.98)
Vol	-1.23369	-1.56632	-1.59206	-1.70840	-1.66248
	(-2.23)	(-2.86)	(-2.83)	(-3.14)	(-3.01)
Max	-0.02373	-0.00580	-0.00731	-0.00018	-0.00243
	(-0.25)	(-0.06)	(-0.07)	(-0.00)	(-0.02)
Illiq	3.33559	3.94337	3.87234	3.83163	3.82017
	(2.93)	(3.21)	(3.23)	(3.22)	(3.13)
N	108303	108303	108303	108303	108303
R-sq	0.04	0.04	0.04	0.04	0.04

Table A4. Investor Reactions to Daily Returns (excluding Hitting Price Limits)

This table reports the results in Table VII for the sample excluding stock-days hitting price limits.

	$Netbuy(New)_{d+1}$	$Netbuy(Gen)_{d+1}$	$Netbuy(L)_{d+1}$	$Netbuy(MF)_{d+1}$	$Netbuy(OI)_{d+1}$
	(1)	(2)	(3)	(4)	(5)
Ret_d	1.33451	-12.13445	-6.46716	13.30376	1.60878
	(8.69)	(-10.66)	(-14.59)	(21.87)	(2.96)
$Ret_{d-5\to d-1}$	-0.00477	-6.19554	0.28078	3.87794	1.18469
	(-0.15)	(-17.50)	(2.02)	(17.56)	(10.50)
$Ret_{d-21\to d-6}$	-0.01388	-0.78741	-0.35766	0.91270	0.06558
	(-1.25)	(-6.77)	(-6.99)	(11.75)	(1.24)
Ln_cap	-0.00185	0.17975	-0.10772	-0.02714	-0.02867
	(-1.27)	(11.75)	(-11.62)	(-2.83)	(-3.45)
Turnover_float	2.21233	12.45005	-6.65482	-3.58673	-3.29977
	(10.02)	(21.02)	(-16.56)	(-10.01)	(-12.37)
BM	0.01149	0.01211	0.11153	-0.07922	-0.01090
	(1.20)	(0.22)	(2.64)	(-2.20)	(-0.41)
Constant	0.04314	-3.07520	1.87670	0.41509	0.47749
	(1.62)	(-12.84)	(12.00)	(2.98)	(3.87)
N	2346739	2346739	2346739	2346739	2346739
R-sq	0.058	0.058	0.046	0.055	0.037

Table A5. Portfolio Sorting Based on New Investors' Trading Volume

This table reports the results of one-day return of double-sorted portfolios. We sort stocks independently into quintiles based on the past one-day return and terciles based on the trading volume by new investors divided by the total trading volume over past 22 trading days. We then report the one-day return for each portfolio, that is value-weighted by market capitalization at the most recent month-end or equal weighted. The return of a portfolio that longs the top quintile of the past one-day return and shorts the bottom is also reported. t-statistics are reported in parentheses.

Value-Weighted

	Q1	Q2	Q3	Q4	Q5	Q5-Q1
	Holding Horizon: 1d					
Low NI Volume	-0.00068	0.00093	0.00130	0.00133	0.00220	0.00288
	(-1.61)	(2.32)	(3.63)	(3.77)	(5.82)	(8.42)
Mid NI Volume	-0.00103	0.00074	0.00083	0.00082	0.00169	0.00272
	(-2.28)	(1.70)	(2.01)	(2.14)	(3.83)	(7.42)
High NI Volume	-0.00216	0.00041	0.00080	0.00061	0.00243	0.00459
	(-4.42)	(0.94)	(1.97)	(1.56)	(4.97)	(10.16)

Equal-Weighted

	Q1	Q2	Q3	Q4	Q5	Q5-Q1
	Holding Horizon: 1d					
Low NI Volume	-0.00039	0.00126	0.00157	0.00145	0.00212	0.00251
	(-0.89)	(3.05)	(3.99)	(3.88)	(5.28)	(7.73)
Mid NI Volume	-0.00089	0.00104	0.00127	0.00092	0.00156	0.00245
	(-1.89)	(2.33)	(2.95)	(2.30)	(3.47)	(6.70)
High NI Volume	-0.00180	0.00069	0.00105	0.00069	0.00319	0.00499
	(-3.67)	(1.53)	(2.45)	(1.70)	(5.86)	(10.08)

Table A6. Correlation of Investor Groups at Daily Level

This table reports the results in the Fama-MacBeth regressions of the *Netbuy* of new investors on the *Netbuy* of other investor groups. t-statistics are reported in parentheses.

	$Netbuy(New)_d$			
	(1)	(2)	(3)	(4)
$Netbuy(Gen)_d$	0.01493	0.00394	-0.02255	-0.13283
	(7.45)	(1.59)	(-4.54)	(-9.45)
$Netbuy(L)_d$		-0.02920	-0.05545	-0.16297
		(-8.13)	(-9.17)	(-11.15)
$Netbuy(MF)_d$			-0.05545	-0.17006
			(-10.18)	(-11.70)
$Netbuy(OI)_d$				-0.16727
				(-11.51)
Ln_cap	0.00396	0.00208	0.00467	0.00249
	(2.44)	(1.45)	(2.54)	(2.61)
Turnover	3.96823	3.86576	3.78405	2.82752
	(14.29)	(14.55)	(15.41)	(19.52)
BM	0.01790	0.02264	0.01713	0.01344
	(1.95)	(2.30)	(2.05)	(3.14)
Constant	-0.07660	-0.04897	-0.08604	-0.05107
	(-2.84)	(-2.05)	(-2.98)	(-3.20)
N	2418806	2418806	2418806	2418806
R-sq	0.13	0.15	0.18	0.29

Table A7. Summary Table of International Markets

This table reports the number of stocks, the sample period, and the market cap in USD for international markets in our sample.

Emerging Markets	Number of Stocks	Start Year	End Year	Market Cap	Developed Markets	Number of Stocks	Start Year	End Year	Market Cap
Brazil	594	1994	2023	476548	Australia	3462	1980	2023	569297
Chile	210	1992	2022	134562	Austria	213	1992	2008	62041
China	5190	1993	2023	3507682	Belgium	425	1984	2023	200117
Czech Republic	181	1994	2001	13641	Canada	7692	1980	2023	903589
Egypt	271	1999	2023	43431	Denmark	450	1988	2023	200592
Greece	487	1990	2023	64926	Finland	331	1994	2023	221498
India	6020	1990	2023	976258	France	1765	1980	2023	1207423
Indonesia	914	1990	2023	211558	Germany	3398	1980	2023	1881316
Israel	1039	1986	2023	109649	Hong Kong	2645	1984	2023	1215160
Malaysia	1418	1986	2023	241064	Italy	874	1986	2023	471580
Mexico	216	1993	2016	188557	Japan	5959	1980	2023	3472638
Pakistan	567	1992	2023	35389	Netherlands	450	1980	2023	379580
Philippines	347	1991	2023	109717	New Zealand	299	1993	2023	50120
Poland	1259	1997	2023	115874	Norway	779	1986	2023	161863
Saudi Arabia	266	2007	2023	859408	Portugal	151	1992	2000	36467
South Africa	920	1990	2023	306772	Singapore	1070	1983	2023	266922
South Korea	3887	1984	2023	643286	Spain	395	1989	2023	492616
Taiwan	2723	1989	2023	656852	Sweden	1791	1982	2023	353762
Thailand	1075	1988	2023	208777	Switzerland	649	1980	2023	717701
Turkey	649	1990	2023	135016	UK	4639	1980	2023	2030005
Vietnam	1632	2007	2023	101723	USA	17901	1980	2023	12936409

Table A8. Daily Price Limit Policy in International Market

This table reports the detail of daily price limit policy in the international market. Note that we only regard the policy limiting the maximum of daily price movement as daily price limit, but exclude the situations of "circuit breaker" or "volatility interruption" which let the price move further after a trading suspension.

Market	Policy implemented or not	Source
Brazil	No	Stock Exchange Factsheets
Chile	No	Bolsa de Santiago.com
China	Yes	Introduction of price limit rules in China
Czech Republic	No	PSE - Trading Rule
Egypt	Yes	EGX - Trading System
Greece	No	Stock Exchange Factsheets
India	Yes	National Stock Exchange
Indonesia	Yes	IDX - Trading Hours and Mechanism
Israel	No	TASE Trading Rules & Regulations
Malaysia	Yes	Bursa Malaysia Securities Berhad
Mexico	No	Electronic trading system rules issued by BMV
Pakistan	Yes	Pakistan Stock Exchange Ltd.
Philippines	Yes	Memorandum of the revised trading rule of PSE
Poland	Yes	The Warsaw Stock Exchange Rules
Saudi Arabia	Yes	Saudi Stocks Basics
South Africa	No	JSE - markets regulation
South Korea	Yes	KRX Regulation - KOSPI market
Taiwan	Yes	Taipei Exchange - Trading Rules
Thailand	Yes	SET - price bands
Turkey	Yes	Borsa Istanbul - Market Functioning
Vietnam	Yes	Securities Trading Rule for HSX
Austria	No	Austria trading system
Australia	No	Australian - market
Belgium	No	EuroNext - market rule
Canada	No	TSX - Rulebook
Denmark	No	Nasdaq Nordic Market Model
Finland	No	Nasdaq Nordic Market Model
France	No	EuroNext - market rule
Germany	No	Deutsche Boerse - Rules
Hong Kong	No	HKEX Rules
Italy	No	Markets Rules - Borsa Italiana
Japan	Yes	JPX - Trading Rules
Netherlands	No	EuroNext - market rule
New Zealand	No	NZX market specification
Norway	No	EuroNext - market rule
Portugal	No	EuroNext - market rule
Singapore	No	SGX - Trading
Spain	No	BME - Regulation
Sweden	No	Nasdaq Nordic Market Model
Switzerland	No	Trading on SIX Swiss Exchange
UK	No	LSE - Rules
USA	No	circuit breaker in US market