Daily Momentum and New Investors in an Emerging Stock Market*

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Abstract

Despite the dominance of retail investors in the Chinese stock market, there's a conspicuous absence of price momentum in weekly and monthly returns. This study uncovers the presence of price momentum in daily returns and, through a systematic analysis of trading heterogeneity among investors, links daily momentum to the attention and trading activities of new investors—a phenomenon particularly significant in emerging stock markets. Furthermore, our findings indicate the existence of daily price momentum in various other emerging markets, contrasting with its relative scarcity in developed ones.

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The joint presence of medium-term price momentum at the horizons of 1-12 months (e.g., Jegadeesh and Titman (1993)) and long-term price reversals at the horizons of 2-5 years (e.g., De Bondt and Thaler (1985)) in the U.S. stock market had precipitated the development of a series of behavioral finance theories, e.g., Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998), and Hong and Stein (1999). These theories highlight various cognitive biases that may influence retail investors and lead to the occurrence of medium-term price momentum and long-term price reversals. These behavioral finance theories are, however, challenged by the lack of medium-term price momentum in the Chinese stock market. As recently reviewed by Song and Xiong (2018), Hu, Pan, and Wang (2021), and Allen, Qian, Shan, and Zhu (2020), the Chinese stock market, despite being the second-largest stock market in the world and listing over 4,700 stocks, is dominated by retail investors and thus most relevant for behavioral finance theories. However, as documented by Chui, Titman, and Wei (2010) and Du, Huang, Liu, Shi, Subrahmanyam, and Zhang (2022), medium-term price momentum does not exist in China and, instead, the past six- and twelve-month returns are negatively correlated with future returns. More generally, Liu, Stambaugh, and Yuan (2019) show that the Chinese stock market features a powerful reversal effect that is robust at the horizons ranging from one, three, six, twelve months to five years.

The noted absence of medium-term price momentum prompts us to examine price dynamics at differing intervals in the Chinese stock market. Our examination reveals reversal patterns in both weekly and monthly returns, reinforcing the nonexistence of medium-term momentum. Contrastingly, we discern a pronounced phenomenon of significant daily price momentum—stocks exhibiting strong performance today are likely to maintain this outperformance tomorrow. This momentum persists for one to two days before exhibiting a reversal within a week and is resilient to both equal/value weighting and the exclusion of stocks encountering daily price limits. Notably, this effect displays asymmetry under varying market conditions, intensifying during bullish markets and diminishing in bearish ones.

Why does price momentum exist in daily, but not weekly/monthly, returns in the Chinese stock market? We address this question by analyzing the reactions of various investor groups to past stock returns and understanding how their trading activities contribute to the observed daily price momentum. By leveraging granular account-level transaction data from the Shenzhen Stock Exchange (SZSE) from 2005 to 2019, we are able to dissect trading activities across all SZSE-listed stocks according to different investor categories. Unlike many stock exchanges around the world, Chinese stock exchanges have a distinct feature: they can track all trading activities of an individual—across various brokerage firms—using the individual's unique national ID.

A key group of interest in our study is the "new investors." Having been established in the early 1990s, the Chinese stock market has witnessed regular influxes of new, inexperienced investors. Such investors, due to their inexperience and potential cognitive biases, are often more reactive to daily market gyrations. This particular trait is not unique to China; it is a phenomenon common across emerging markets, underscoring the importance of investigating the trading behaviors of new investors. For the purpose of this study, we define new investors as those who initiated their accounts within the last three months and executed at least one stock trade during the period.

Beyond new investors, our study also categorizesretail investors into two additional groups based on their account balances: "experienced retail investors" with balances under three million RMB and "large retail investors" with balances exceeding three million RMB. On the institutional side, we delineate between mutual funds and other institutions. To obtain a holistic view, we track the net buying of these five distinct groups for every SZSE-listed stock, every trading day.

Both new investors and experienced retail investors stand out with striking daily turnover rates of 18.12% and 8.03%, respectively. Furthermore, their monthly net buying of a stock tends to negatively predict stock returns in subsequent months. This combination of high trading intensity and poor stock selection makes these two groups noise traders in the Chinese stock market. It's noteworthy that the new investor group essentially acts as a heightened representation of noise traders; the only distinction between them and the experienced retail investors is the somewhat arbitrary 3-month trading experience threshold. In contrast, the remaining groups—large retail investors, mutual funds, and other institutions—demonstrate a more modest turnover rate. More crucially, their monthly net buying tend to serve as a positive predictor of stock returns in the subsequent months, suggesting superior stock selection skills.

To identify the group instrumental in driving the observed daily price momentum, we delve deeper than just observing the daily net buying patterns of each investor group in response to the previous day's stock returns. Crucially, we investigate if there's a correlation between a stock's current day return and the interaction between its past day return and a specific group's net buying activity on the current day. This method offers a direct link between a stock's daily price momentum and an investor group's trading behavior in response to the stock's return from the preceding day.

Intriguingly, our analysis reveals that new investors' daily net buying behavior has a positive correlation with stocks' returns from the previous day. Moreover, the combined effect of a stock's return from the day before and new investors' net buying on the present day is positively associated with the stock's current day return. Yet, this combined effect also has a negative correlation with the stock's returns over the subsequent weeks. This finding strongly suggests that new investors are central to the observable daily price momentum and the following price reversals.

Conversely, our analysis indicates that large investors play a role in counterbalancing the observed price momentum. Their daily net buying activities show a negative correlation with the stocks' returns from the preceding day. Additionally, the interaction between a stock's return from the previous day and large investors' net buying on the current day has a negative correlation with the stock's return on that day and positive correlations with the stock's returns in the subsequent weeks.

Our analysis also unveils some more nuanced insights. While mutual funds' daily net buying aligns positively with stocks' prior-day returns, suggesting a momentum trading pattern, the story evolves when we delve deeper. The interplay between a stock's previous day return and the mutual funds' net buying on the current day correlates negatively with the stock's return on that very day. However, it aligns positively with the stock's returns in the subsequent week and month. This important observation underscores that, despite initial appearances, mutual funds play a role in tempering the observed price momentum, acting as a counterbalancing force.

Taken together, we find that new investors and experienced retail investors significantly contribute to daily price momentum and subsequent price reversal, while the other three groups—large investors, mutual funds, and other institutions—counterbalance these price effects. The contribution from new investors is especially pronounced.

The phenomenon of daily price momentum is not exclusive to the Chinese stock market. We've also probed its existence in major markets around the world, including 21 emerging and 21 developed markets. Remarkably, we identified value-weighted daily price momentum in 14 of the emerging markets, but in only 3 of the developed ones. Furthermore, many of these markets with daily momentum effects show a comparable asymmetry between bullish and bearish periods, mirroring the trend seen in the Chinese market.

While the presence of new investors is evident in other emerging markets, the lack of granular account-level data hinders a direct exploration into the connection between the observed price momentum and the trading behaviors of these new investors. Yet, the significant occurrence of daily price momentum in these emerging markets lends weight to the notion of new investors exerting a meaningful influence. It's plausible that the intensified trading activity of these new investors during bullish periods amplifies the observed asymmetric patterns in those emerging markets that display daily momentum effects. Collectively, these international observations suggest a widespread existence of the daily momentum phenomenon and underscore the significant role of new investors across multiple emerging markets.

This paper contributes to the studies of stock price momentum, e.g., Jegadeesh and Titman (1993). Although the medium-term (3 to 12 months) price momentum is well documented in many countries around the world (Rouwenhorst (1998) and Griffin, Ji, and Martin (2003)), the Chinese stock market remains a notable exception, as higlighted by Chui et al. (2010) and Du et al. (2022). In this study, we not only corroborate the absence of medium-term price momentum in China but more importantly document a previously undocumented phenomenon: the presence of price momentum in daily returns. Furthermore, by systematically analyzing the roles played by all investor groups, we attribute this novel daily price momentum to the trading behaviors of new investors, thereby demystifying a significant conundrum in the world's second-largest stock market.

This paper further complements the existing body of literature on retail investors, a domain extensively reviewed in Barber and Odean (2013). Our contribution is particularly salient in the context of emerging markets, where considerable research has focused on two markets: China and India. For insights into the Indian market, see Balasubramaniam, Campbell, Ramadorai, and Ranish (2023), Anagol, Balasubramaniam, and Ramadorai (2021), and Campbell, Ramadorai, and Ranish (2019). Meanwhile, the Chinese realm has been detailed in works like Chen, Gao, He, Jiang, and Xiong (2019), Jones, Shi, Zhang, and Zhang (2020), An, Lou, and Shi (2022), Liu, Peng, Xiong, and Xiong (2022), and Liao, Peng, and Zhu (2022). A recurrent theme across these studies is the discernible heterogeneity in both trading behaviors and performance of Chinese retail investors when stratified by their account balances, albeit not new investors. Different from these studies, we systematically compare the contributions of new investors and other investor groups to daily price momentum. This phenomenon, not just novel to the Chinese market, but also finds echoes across several other emerging markets, further accentuating the significance of our findings.

Our paper is also related to the literature on investment experience. Greenwood and Nagel (2009) study the behaviors of inexperienced versus experienced fund managers during the tech bubble. Using manager age to proxy for their experience, they find that younger managers tend to be trend chasers and perform poorly in the tech stock investment. In addition, Nicolosi, Peng, and Zhu (2009) and Seru, Shumway, and Stoffman (2010) examine retail investors' self-learning from trading experiences. Our paper identifies new investors without any stock trading experience based on the history of their brokerage accounts and focuses on asset pricing implications of new investors.

Our paper also contributes to the literature on noise trading. Noise traders are referred to as investors who respond to noise rather than fundamental information (Kyle (1985) and Black (1986)). As a key concept in modern finance, noise trading plays an important role in numerous models of explaining market dynamics (e.g.,De Long, Shleifer, Summers, and Waldmann (1990a,b), Campbell and Kyle (1993), and Stambaugh (2014), among many others). The empirical literature generally regards retail investors as noise traders and studies their effects on mispricing in financial markets (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), among many others). In this paper, we highlight important heterogeneity among retail investors and highlight the trading of new investors as a more reliable measure of noise trading.

An emerging literature has analyzed stockholders' characteristics and their implications to investment portfolios and asset prices. Using Indian data, Balasubramaniam et al. (2023) find that individual investors' portfolio exhibits a strong factor structure. Betermier and Sodini (2017) link stockholders' demographics to their portfolio exposures to the value factor. Betermier, Calvet, Knüpfer, and Soerlie Kvaerner (2022) find that investor wealth and age are the two useful characteristics that could drive investors' portfolio choices and the cross-section of stock returns. We complement these studies by showing that investors' inexperience can explain a rich set of return predictability in the Chinese stock market.

The structure of our paper is delineated as follows: Section I delves into the existence of price momentum across various timelines within the Chinese stock market. In Section II, we present findings connecting the discerned daily price momentum to the trading behaviors of new investors and other investment groups. Section III extends our analysis to assess the daily momentum phenomenon in major emerging and developed markets globally. We conclude the paper in Section IV.

I. Price Momentum

In this section, we examine possible momentum effects over different horizons in the Chinese stock market. We collect daily, weekly, and monthly stock return data from the China Stock Market and Accounting Research (CSMAR) database. This sample covers stocks from both the Shanghai Stock Exchange and the Shenzhen Stock Exchange, the two major stock exchanges in China, from 2005 to 2019.

Motivated by the well-known medium-term price momentum found in the U.S., we first analyze monthly stock returns in the Chinese stock market. To investigate return predictability, we run Fama-MacBeth regressions as follows:

$$Ret_{i,m+1\rightarrow m+j} = Constant + c_1 Ret_{i,m} + c_2 Ret_{i,m-11\rightarrow m-1} + Controls_{i,m} + \epsilon_{i,m+1}, \quad (1)$$

where we consider the predictability of the current month return $Ret_{i,m}$ and the past 11-month return $Ret_{i,m-11\rightarrow m-1}$ for the future 1-, 3-, and 6-month (j=1, 3, or 6) stock returns, respectively. We also control for a battery of stock-level characteristics, including market capitalization (Ln_cap), abnormal turnover rate of floating shares ($Abn\_turnover$), book-to-market ratio (BM), daily return volatility in the current month (Vol), maximum daily return in the month (Max), and illiquidity measured by the average ratio of the absolute value of daily return to volume ($Illiq$). If medium-term price momentum exists, we should expect the coefficient before the cumulative return in the past eleven months $Ret_{i,m-11\rightarrow m-1}$ to be significantly positive.

Regression results are reported in Panel A of Table I. The coefficients on returns are either significantly negative or insignificant. In column (1), for example, the coefficient on current month return $Ret_{i,m}$ is -0.026 (with a t-stat of 2.68) and the coefficient on $Ret_{i,m-11\to m-1}$ is insignificant. This indicates the absence of medium-term momentum in the Chinese stock market, which is in contrast to the price momentum observed in the U.S. over 3-12 month horizons. Notably, the Chinese stock market exhibits a significant monthly turnover pattern.

Next, we shift our focus to a shorter time horizon and examine weekly returns. We conduct the following Fama-MacBeth regressions:

$$Ret_{i,w+1\to w+j} = Constant + c_1 Ret_{i,w} + c_2 Ret_{i,w-3\to w-1} + Controls_{i,w} + \epsilon_{i,w+1}, \tag{2}$$

where we regress the future 1-, 2-, and 3-week (j=1, 2, or 3) stock returns, respectively, on both the current week return as well as the previous 3-week return. Panel B of Table I reports the regression results. Once again, we observe the absence of price momentum in weekly returns in the Chinese stock market. Notably, Panel B reveals a distinct pattern of weekly reversals, with all coefficients on the current week return and the previous 3-week return for predicting future 1 to 3-week returns being significantly negative.

Lastly, we delve into the analysis of daily stock returns to determine the existence of a momentum pattern. We specifically conduct the following Fama-MacBeth regressions:

$$Ret_{i,d+1} = Constant + c_1 Ret_{i,d} + c_2 Ret_{i,d-5\to d-1} + c_3 Ret_{i,d-21\to d-6} + Controls_{i,d} + \epsilon_{i,d+1}, \tag{3}$$

where we perform the regressions of the future stock returns over one day ($Ret_{i,d+1}$) on returns on day 0 return ($Ret_{i,d}$), over previous five days ($Ret_{i,d-5\to d-1}$), and from Days -21 to -6 ($Ret_{i,d-21\to d-6}$). We also replace the dependent variable with returns over days 2 to 6 ($Ret_{i,d+2\to d+6}$) and returns over days 2 to 11 ($Ret_{i,d+2\to d+11}$) to examine the reversal effect. We report the results in Panel C of Table I. The first column of Panel C shows that the coefficient on $Ret_{i,d}$ is positive (with a t-stat of 7.54). The coefficient on the past five-day return $Ret_{i,d-5\to d-1}$ turns out to be negative (with a t-stat of 24.92), and the coefficient on $Ret_{i,d-21\to d-6}$ is also significantly negative (with a t-stat of 17.73). The overall pattern suggests that price momentum exists in daily stock returns and quickly reverses. In the second column, we examine the stock return in the following week (skipping the day $d+1$), $Ret_{i,d+2\to d+6}$, on the left-hand side. The coefficient of $Ret_{i,d}$ turns out to be negative and significant (with a t-stat of 21.09), suggesting a strong reversal pattern. The coefficients of $Ret_{i,d-5\to d-1}$ and $Ret_{i,d-21\to d-6}$ remain significantly negative. In the third column, the left-hand side variable is the stock return in the following month (skipping the day $d+1$). The results are similar: all three past return variables appear to be negatively related to the subsequent month's return. Throughout the three columns, the coefficients of *Ln_ cap*, *BM*, and *Turnover* suggest small, value, and less traded stocks appear to have higher returns, consistent with the previous studies.

We have also applied the original portfolio sorting method developed by Jegadeesh and Titman (1993) to study price momentum and reversal at monthly, weekly, and daily horizons, respectively. The patterns observed align with the findings obtained from the Fama-MacBeth regressions. In the Internet Appendix, Table A1 reports the results for monthly returns. We sort stocks based on returns over the past one, three, six, and twelve months and construct long-short portfolios (both value-weighted and equal-weighted). The future one-month returns of the long-short portfolios are all negative, suggesting price reversals across these medium-term horizons rather than momentum, confirming the lack of medium-term price momentum in the Chinese stock market previously documented by Chui et al. (2010) and Du et al. (2022). We further examine the return dynamics at weekly horizons in Table A2 of the Internet Appendix. The sorting portfolios based on the past one to eight weeks again display price reversals rather than momentum in the subsequent weeks, for both value-weighted and equal-weighted sorting.

We report the portfolio sorting results for daily returns in Table II. We sort stocks based on their returns in the past one to ten days and present the returns of long-short portfolios over the subsequent one to ten days. As shown by Panel A, there is a pronounced momentum effect in daily stock returns, which lasts for one day before a reversal. For example, the long-short portfolio based on the sorting returns from the previous day earns a positive one-day return of 0.37%. This magnitude is substantial as multiplying this daily return by 250 (the number of trading days in a year) leads to a staggering annual return of 92.5%.

It is important to note that transaction cost and microstructure effects work against finding price momentum. There is a well-known effect of bid-ask bounce creating a negative serial correlation in daily stock returns, e.g., Roll (1984). This bid-ask bounce effect works directly against any price momentum in daily returns, making our finding of the significant price momentum even more impressive. Thus, the underlying price momentum in daily returns must be sufficiently strong to overcome the negative serial correlation generated by the potential bid-ask bounce effect.

The momentum in the daily returns quickly reverses. Holding the long-short portfolio longer for two days leads to a cumulative return of 0.30%, indicating a weak reversal already on the second day. Holding the portfolio longer leads to even lower cumulative returns. The patterns in daily price momentum and subsequent reversals are robust to both value-weighted and equal-weighted portfolios.

As the Chinese stock market imposes limits on daily price changes for individual stocks, as studied by Chen et al. (2019), it is possible that the price limits curb daily price changes and thus lead to a mechanical continuation of stock prices after hitting the daily price limits. To address this issue, we exclude stock-day observations with daily stock returns hitting either the upper or lower daily price limits and report the results in Panel B of II. The magnitude of return continuation indeed decreases, suggesting the influence of price limits on daily momentum. However, the magnitude remains statistically and economically significant, underscoring the robustness of the daily price momentum pattern in the Chinese stock market.

Taken together, our results confirm the absence of price momentum in monthly and weekly stock returns. More importantly, we find a significant price momentum effect in daily stock returns. That is, stocks with higher returns today are likely to outperform on the next day as well. Interestingly, this price continuation pattern reverses in a few days. Furthermore, there are prevalent price reversals for longer horizons, ranging from one week to twelve months.

In the next section, we will use account-level transaction data from the Shenzhen Stock Exchange to examine how the trading of different investor groups reacts to past returns and how the observed daily price momentum is related to the trading of new investors.

II. New Investors and Daily Momentum

Reopened in the early 1990s, the Chinese stock market is predominantly occupied by retail investors and is characterized by frequent influxes of new investors, a common trait among emerging markets. These new investors, possessing limited investment experience, are prone to cognitive biases and susceptible to the emotional impacts of market fluctuations. In this section, we utilize account-level data from the SZSE to sort investors into different groups and assemble trading data pertinent to each group. This holistic dataset enables us to analyze how the observed daily momentum is related to the trading activities of not only new investors but also other investor groups.

Per Chinese regulations, brokerage firms are mandated to disclose the associated brokerage accounts involved in every transaction to the stock exchange—a stark contrast to standard practices in other countries where exchanges typically lack insight into the accounts conducting the transactions via brokerage firms. In the SZSE, individual retail accounts are uniquely identified through the national ID number of the account holder. Consequently, the SZSE maintains transaction records for each investor, enabling the tracking of new investors, even those possessing multiple accounts across various brokerage firms.[1] This meticulous record-keeping allows tracking of the trading behaviors of each individual in this market.

[1] As of April 13, 2015, investors in China have been permitted to maintain multiple accounts with different brokerage firms.

Specifically, we divide all accounts into three retail investor groups and two institutional investor groups, spanning from 2005 to 2019. Each month, we designate new investors as those with retail accounts opened within the preceding three months. The experienced retail investors are further separated into two subsets based on account balance value: normal (*Exp*)—those with less than three million RMB and large (L)—those exceeding three million RMB. Consequently, we delineate the retail investor domain into three subsets: *New*, *Exp*, and L. There are also two institutional investor groups: mutual fund (MF) and other institutions (OI).[2]

A. New Investors as Noise Traders

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

We first present the demographic information of new investors in Panel A of Table III, comparing the average age of new and all retail investors over time. We observe that new investors tend to be significantly younger than the average retail investor, and this age difference persists over the sample years. Regarding gender composition, also illustrated in Panel A, male investors are slightly more prevalent, but the gender distribution among new investors and overall retail investors does not significantly differ.

In Panel B, we report the turnover rates of new investors, juxtaposing the average daily turnover rates of other investor groups.[3] Aligning with the extensively documented high trading intensity of Chinese investors, as reviewed by Liu et al. (2022), all three retail groups exhibit exceptionally high daily turnover rates. New investors display the highest level of trading involvement with an average daily turnover rate of 18.12%, translating to an annual rate of roughly 4500%. Although lower, the daily turnover rates of experienced and large

[2] The large retail investor group may also encompass accounts opened within the recent three months. This subset is marginal; therefore, we abstain from subdividing large investors into two discrete groups by account age.

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

investors, standing at 8.03% and 3.26% respectively, are markedly higher than the trading intensity demonstrated by retail investors in the U.S., as noted by Odean (1999).

At the aggregate market level, we construct the fraction of all new investors each month, scaled by the number of all active investors in the SZSE, referred to as *frac_ni*. At the individual stock level, for each of the five investor groups, we calculate *Netbuy* for a stock, defined as the total value of purchases minus sales by the group over a month, normalized by the stock's float capitalization from the preceding month. We also obtain other stock-level data from CSMAR, 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.

We list the definitions of the variables used in this section in the Appendix. Table A3 of the Internet Appendix summarizes the key statistics of these variables. Panel A reports the summary statistics of the variables for the whole SZSE market over time. Panels B and C present statistics of the variables for the stock level analyses, including all A-share stocks traded in the SZSE at monthly and daily frequencies, respectively.

The average fraction of new investors is 3.7% in our sample period. However, its variation over time is pronounced, as depicted in Figure 1. From 2005 to 2019, the ratio of new investors (*frac_ni*) in the market experiences remarkable cycles. The two substantial surges of new entries were witnessed in 2007 and 2015, aligning well with the two largest market booms in the history of the Chinese stock market. There is a close relationship between the entries of new investors and the boom-and-bust cycles of the stock market: a market boom comes with a sharp increase in the entry of new investors, while a market collapse is accompanied by a rapid drop in new account openings.[4]

To compare the stock selection ability of different investor groups, we examine the return predictability of the trading of each investor group at monthly horizons. Specifically,

[4]Table A4 in the Internet Appendix offers supplementary analysis, illustrating that the ratio of new investors (*frac_ni*)possesses significant and negative predictive power for market return in the following 1, 3, 6, and 12 months. This suggests the poor market timing ability of new investors.

we conduct Fama-MacBeth regressions of the future one-month stock returns on the *Netbuy* of different investor groups. Table IV presents the results.

Column (1) shows that the return predictability of the net buying by new investors is significantly negative, suggesting that new investors' net buying tends to be followed by a loss on average in the subsequent month. The magnitude is also economically significant: a one-standard deviation of the *Netbuy*(*New*) is associated with a 1.73% (= 0.347% × 5.0) decrease in the return next month. Column (2) shows that the *Netbuy* of experienced investors (*Exp*) also predicts a significantly negative return: a one-standard-deviation of the *Netbuy* of experienced investors is associated with a 0.96% (= 0.032% × 30.6) decrease in the return next month. Even though this group is more experience in stock trading, they also tend to purchase stocks that underperform in the subsequent month.

Columns (3), (4) and (5) show that the trading of large retail investors (L, with a stock balance of more than three million RMB), mutual funds, and other institutional investors all displays positive predictability of the future one-month stock return: a one-standard-deviation of the *Netbuy* of these groups is associated with 0.63% (= 0.038% × 16.5), 0.21% 0.46% (= 0.021% × 22.0) and 0.31% (= 0.018% × 17.5) increase in the future one-month return, respectively. These results suggest that these groups have stronger ability to select stocks than new investors and experienced retail investors.[5] [6]

Taken together, it is evident that new investors demonstrate the highest turnover rate and the most inferior stock selection skills. However, it is also pertinent to note that experienced retail investors, too, engage in extensive trading and exhibit poor stock selection ability, although not as pronounced as that of new investors. The remaining three groups—large

[5]Several stock-level control variables also have predictability for future returns. The coefficients of these control variables suggest that small, low-turnover, and value stocks tend to outperform large, high-turnover, and growth stocks. There is also a significant one-month return reversal effect. Moreover, stocks with high maximum daily returns and high liquidity tend to have lower future one-month returns.

[6]In Table A5 of the Internet Appendix, we also report the results for predicting the subsequent three-, six-, and twelve-month returns. The results are consistent for longer horizons: the *Netbuy* of both new and experienced investors predicts negative future returns over three, six, and twelve months, and the magnitudes accumulate over longer horizons. Large investors' *Netbuy* positively predicts the future returns over three, six, and twelve months. The *Netbuy* of the retail investors as a whole has insignificant predictability for future returns over different horizons.

retail investors, mutual funds, and other institutions—all exhibit strong stock selection capabilities, with large retail investors demonstrating the most pronounced ability.[7]

In Figure 2, we further dissect the contribution of each of the five investor groups to the trading volume. Although new investors exhibit a remarkable turnover rate, they contribute modestly to the total trading volume, 2.01%, attributed to their limited market share. In contrast, the experienced investor group commands the most significant slice of the trading volume, contributing 65.4%, due to encompassing the largest number of investors. It's noteworthy that the demarcation between the new and experienced investor groups is solely an arbitrary cutoff set at 3-month trading experience. Consequently, new investors simply serve as a more prominent representation of noise traders.

B. Reactions of Different Groups to Past Returns

The behavioral finance literature has highlighted several cognitive biases of investors as potential drivers of price momentum, such as extrapolative beliefs (e.g., Barberis et al. (1998) and overconfidence (e.g., Daniel et al. (1998)). To the extent that new investors lack trading experiences and are excitable by market fluctuations, they are more vulnerable to these biases than other investors. We now examine how each investor group trades in response to past stock returns. We focus on trading at the daily frequency so that we can relate their trading to the observed daily price momentum.

Specifically, we regress the *Netbuy* of a stock by each investor group $Netbuy_{i,d+1}$ onto three non-overlapped 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

[7]Extensive evidence underscores large retail investors as smart traders in the Chinese stock market. Chen et al. (2019) analyzes market dynamics when the prices of individual stocks approach the daily 10% price limits. The study reveals that large investors generally acquire stocks right before they hit price limits and then sell them to smaller investors on the subsequent day, securing a profit. Additionally, An et al. (2022) illustrate how the boom-and-bust cycle in the Chinese stock market during 2014–2015 accentuated wealth disparities between large and small retail investors.

week ($Ret_{i,d-21\to d-6}$),

$$Netbuy_{i,d+1} = Constant + c_1 Ret_{i,d} + c_2 Ret_{i,d-5\to d-1} + c_3 Ret_{i,d-21\to d-6} + Controls_{i,d} + \epsilon_{i,d+1}. \quad (4)$$

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

Table V shows that the five groups manifest distinctly varying responses to past returns. As anticipated, Column (1) reveals that new investors are momentum traders—their *Netbuy* exhibits a significant and positive reaction to the past day return and the past week return but adopts a negative stance, albeit insignificantly, to the past month return. In contrast, Columns (2) and (3) depict that both experienced and large retail investors operate as contrarian traders. Their *Netbuy* responds negatively to the past returns at three different lags, with the exception being the insignificantly positive reaction of large investors to past week return.

Column (4) also indicates that mutual investors collectively behave like momentum traders, their responses to past day, past week, and past month returns being uniformly and significantly positive. The reaction of the fifth group, other institutions, as outlined by Column (5), is more ambiguous, showing insignificant reactions to past day and past month returns but a significantly positive reaction to past week return.

The reaction to past day return is especially noteworthy in analyzing the mechanisms underlying the observed daily price momentum. Table V shows that both new investors and mutual funds align in their positive reactions to the past day return, while experienced and large investors assume opposing positions. The juxtaposition of large investors trading counter to new investors is somewhat expected, but it is rather surprising to witness mutual funds—which also exhibit considerable stock selection capability—not opposing the trades of new investors and, instead, chasing past returns. This trading pattern suggest a trading strategy divergent from that of large investors. The evident contrast in responses to past day return between experienced retail investors and new investors is also unexpected. Nevertheless, it is useful to acknowledge that the group of experienced investors encapsulates a diverse array of retail investors, potentially muddling the aggregate group behavior.

C. Which Group Drives Daily Price Momentum?

The analysis in the preceding subsection has revealed that both new investors and mutual funds exhibit positive reactions to the past day return. Does the trading activity of these groups propel the observed daily price momentum? For a group's trading to be a catalyst for daily momentum, we would anticipate that the group's trading activities today, in response to a stock's past day return, would elevate 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 of its past day return with the group's current day trading of the stock. Moreover, we would also expect a relation between the stock's subsequent price reversal and this interaction.

We use this strategy to analyze how the observed daily price momentum is related to the trading of each investor group. Specifically, we adopt the following regression specification:

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

The key variable of interest is the interaction term between $Ret_{i,d}$ and $Netbuy_{i,d+1}$. We also include the same control variables as before: size (Ln_cap), book-to-market ratio (BM), and turnover rate ($Turnover\_float$).

Table VI reports the regression results for all of the groups. Panel A focuses on new investors. The first column illustrates a significant and positive relationship between a stock's current day return and the interaction of its past day return with new investors' current day trading of the stock. Additionally, in the second and third columns, we replace the dependent variable of equation (5) with returns over days 2 to 6 and days 2 to 11, respectively. The results show that this interaction term tends to have a significantly negative relationship with the stock's subsequent one-week and one-month returns. Consequently, this panel delivers coherent evidence suggesting that the trading activities of new investors in response to the past day return are correlated with both the daily price momentum and the subsequent price reversal.[8]

Panel B reports the regression results for experienced retail investors, denoted as *Exp*. Intriguingly, the interaction of a stock's past day return with experienced investors' current day trading of the stock manifests a positive correlation with the stock's current day return and a negative correlation with the stock's subsequent one-week and one-month returns. These statistically significant correlations imply that the trading of experienced investors, in reaction to the past day return, also plays a role in shaping the daily price momentum and the following price reversal.

This finding is unexpected, given that this group exhibits a negative response to the past day return, a point discussed in the preceding subsection. We postulate that this can be attributed to the heterogeneity within the group classified as experienced investors. Given the expansive nature of this group, it is plausible that some investors within it barely meet the threshold of possessing three months of trading experience and consequently, may exhibit trading patterns akin to those of new investors. The trading of these relatively inexperienced investors within the group may be a contributing factor to the observed daily momentum, despite the overarching negative reaction of the entire group to the past day return.

In Panels C to E, we report the relationship between daily price momentum and the trading activities of large retail investors *L*, mutual funds *MF*, and other institutions *OI*,

[8]In Table A6 of the Internet Appendix, we use a portfolio sorting method to explore the link between new investors' trading activities and the daily momentum effect. We sort stocks into quintiles based on past one-day returns and terciles based on the ratio of trading volume by new investors to the total trading volume over the last 22 trading days. We then calculate the one-day return for each portfolio, either value-weighted by recent market capitalization or equal-weighted. Corresponding with our regression analyses, a heightened daily momentum effect is evident for stocks heavily traded by new investors. Both 'winner' and 'loser' portfolios maintain their trajectories into the next day, with more significant price continuations observed when they are predominantly traded by new investors. These findings underscore the pivotal role of new investors in enhancing price momentum in daily stock returns.

respectively. A uniform pattern emerges across the regression results for all three groups: the interaction of a stock's past day return with each group's current day trading of the stock is positively correlated with the stock's current day return and negatively correlated with the stock's ensuing one-week and one-month returns. All these relationships hold statistical significance, indicating that these groups play a role in the counteraction of the observed daily price momentum and the subsequent price reversal.

The contribution of mutual funds to the counteraction of the daily price momentum is particularly unexpected, especially considering their previously discussed positive response to past day return. This revelation implies that, although mutual funds have a propensity to acquire recent winners, their trading activities do not instigate further price continuation and ultimately contribute to reversal. This aligns with the prior observation that mutual funds demonstrate significant stock selection ability.

In Table A7 of the Internet Appendix, we also provide additional results from the Fama-MacBeth regressions of the *Netbuy* of new investors on that of other investor groups. The results confirm that across different stocks, the trading activities of new investors demonstrate a significant and positive correlation with those of experienced retail investors. In contrast, significant and negative correlations are observed with the trading of large retail investors, mutual funds, and other institutions. These correlations are consistent with the different patterns in the contributions of new investors and other groups to the observed daily price momentum.

Finally, in Panel F, we incorporate four investor groups—new investors *New*, experienced investors *Exp*, large retail investors *L*, and mutual funds *MF* into the same regressions to conduct a comparative analysis of their effects in a "horse race." Since the contribution of other stakeholders (such as blockholders, insiders, etc.) to the trading volume is negligible, as demonstrated in Figure 2, we exclude other institutions *OI* from these regressions to avoid multicolinearity. Of all the interactions studied, the interaction between the current day trading of new investors and the past day return of a stock maintains significant correlations with both the stock's daily price momentum and the subsequent reversal. The *Netbuy* of experienced investors follows similar patterns to new investors, albeit with much smaller impacts on price dynamics. The influences of the other groups, including large retail investors and mutual funds, are either insignificant or in the opposite direction in this comparative framework. These findings accentuate the distinctive and robust contribution of new investors along with experienced retail investors to the observed daily price momentum and subsequent price reversal.

In conclusion, Table VI demonstrates that new investors and experienced retail investors significantly contribute to daily price momentum and subsequent price reversal. In contrast, the other three groups—large investors, mutual funds, and other institutions—appear to counterbalance these price effects. The contribution from new investors is especially robust and pronounced. Hence, we ascribe the observed price momentum primarily to the trading behavior of new investors, alongside some investors within the experienced investor group who exhibit trading patterns akin to those of new investors.[9]

D. Price Momentum across Different Market Conditions

Why is there such a swift reaction to daily stock returns from new investors in China? This rapid response starkly contrasts with the frequency implied by monthly price momentum noted in more mature stock markets, such as the U.S. market. Casual observations indicate that this quick reaction can be attributed to the intense attention Chinese investors, especially new investors, devote to following stock market fluctuations. The emotions elicited by gains and losses stemming from these fluctuations tend to be particularly engrossing for new investors, who often lack the experience and discipline to differentiate stock trading from other endeavors. This concept aligns with numerous news reports detailing investors spending excessive time monitoring, deliberating, and trading stocks. The extraordinarily high turnover rate of new investors further mirrors their intense focus on the stock market.

[9]A subtler implication of Table VI is that, amongst the five groups in our sample, none seems to employ a 'pump and dump' strategy to inflate prices before a full reversal occurs, as modelled by De Long et al. (1990b) and Hong and Stein (1999).

Due to the lack of data that directly measure investors' attention to the stock market, we adopt an indirect approach to further examine whether the observed daily price momentum is associated with investor attention. The existing literature on investor attention, such as Sicherman, Loewenstein, Seppi, and Utkus (2016), shows that retail investors tend to pay closer attention to the market following positive returns. Consequently, we expect the daily price momentum, driven by the trading of new investors, to be more pronounced during periods of elevated market returns, wherein new investors are likely to pay more attention to the stock market.

In Table VII, we examine the variations in daily price momentum and the trading activities of new investors under conditions of high and low market returns. We categorize conditions as "Market up" when the daily market return is above the median, and "Market down" when it is below the median.

Columns (1) and (2) detail the patterns of daily price momentum in both "Market up" and "Market down" conditions. We observe a consistent presence of daily price momentum in both market rises and falls. Crucially, an asymmetry in the daily price momentum is apparent: the effect is more potent during "Market up" conditions.

Columns (3) and (4) provide the results from regressing the *Netbuy* of new investors on the past day, past week, and past month returns, distinguishing between "Market up" and "Market down" conditions. As expected, the trading of new investors is more responsive to the past day return during "Market up" conditions. Fascinatingly, their trading reactions to past week and past month returns also intensify under "Market up" conditions. In column (3), the coefficient on $Ret_{i,d-5\rightarrow d-1}$ is notably positive and significant during "Market up", yet it loses significance in column (4) under "Market down" conditions. The coefficient on $Ret_{i,d-21\rightarrow d-6}$ persists as positive albeit insignificant during "Market up," contrasting with "Market down" conditions, where it turns significantly negative. This implies that new investors alter their trading strategies more swiftly when the market return is diminishing.

In columns (5) and (6), we examine the connection between daily price momentum and the trading activities of new investors across "Market up" and "Market down" conditions. We focus on the interaction term between $Ret_{i,d}$ and $Netbuy_{i,d+1}$. A positive coefficient suggests that momentum trading by new investors is propelling price continuation into the following day. We find that the coefficient in the regression under "Market up" conditions is greater than that under "Market down" conditions.

Integrating these observations, we conclude that new investors manifest a heightened inclination towards chasing daily price trends in upbeat market conditions compared to downturns. Furthermore, their trading propensities exert a more pronounced influence on daily price momentum during periods of elevated market returns.

In the next section, we transition our emphasis towards international markets, conducting a systematic analysis of the daily price momentum effect across major developed and emerging markets globally. While we lack access to trading data of new investors in these markets, we can still examine the differences in price momentum between up and down market conditions. As illustrated in Table VII, we expect to observe asymmetric patterns should price momentum be present and if new investors display elevated enthusiasm under bullish market conditions.

III. Daily Momentum in International Markets

Is the phenomenon of daily price momentum a characteristic exclusive to the Chinese stock market? In this section, we delve into the prevalence of daily momentum across both major emerging and established markets globally. Our source for international stock return data is DataStream, which covers the sample period from 1980 to 2023. Impressively, DataStream's database encompasses over 100,000 stocks from nearly 200 countries. It's noteworthy, however, that previous literature has raised concerns regarding potential data inaccuracies within DataStream. To address these concerns and ensure the accuracy of our analysis, we employ a winsorizing technique on raw returns, capping them at the top and bottom 2.5% for each day on every exchange. Following Hou, Karolyi, and Kho (2011) and

Ince and Porter (2006), we also exclude instances of missing data and zero daily returns, keeping in mind DataStream's practice of repeating the last valid data entry for firms that have been delisted.

We combine two recognized lists of emerging markets as referenced in academic literature: Fama and French (2012) and Karolyi and Wu (2018). This consolidated list enumerates 27 emerging markets in addition to China: Argentina, Brazil, Chile, Colombia, Czech Republic, Egypt, Greece, Hungary, India, Indonesia, Israel, Malaysia, Mexico, Pakistan, Peru, Philippines, Poland, Qatar, Russia, Saudi Arabia, South Africa, South Korea, Taiwan, Thailand, Turkey, Venezuela, and Vietnam. For a robust analysis of the daily momentum phenomenon, we set a criterion requiring a stock market to boast a minimum of 100 stocks for a continuous period of five years. Adhering to this standard, our final selection narrows down to 21 emerging markets: 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.

As comparative purposes, we also assemble data for a set of developed markets, applying an analogous selection criterion. The final list includes 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 A8 of the Internet Appendix reports the number of stocks, the specific sample period, and the market cap for each market in our sample.

For each market on any given day, stocks are sorted into quintiles based on their daily returns. Subsequently, the next day's portfolio return is calculated, either value-weighted by the market capitalization from the most recent month's end or equal-weighted. We report the return of a strategy that involves taking a long position in the top quintile and a short position in the bottom quintile. Additionally, we employ Newey-West standard errors with a 21-day lag for our calculations.

Table VIII reports the daily returns of the momentum portfolio across the stock markets in our sample. Out of the 21 emerging markets, 14 of them exhibit significantly positive value-weighted daily momentum patterns, including Chile, China, Czech Republic, Egypt, Greece, Israel, Mexico, Pakistan, Saudi Arabia, South Africa, South Korea, Taiwan, Turkey, and Vietnam. The average daily returns of the momentum portfolios in these markets are also substantial, ranging from the lowest 0.13% in China to the highest 1.56% in the Czech Republic. Additionally, 10 of these markets also display significant equal-weighted daily momentum patterns. Also note that six markets exhibit significant value-weighted daily reversal effects, while this number rises to ten when considering equal-weighted daily reversals.

In contrast, among the 21 developed markets in our sample, merely three—Austria, the Netherlands, and the U.K.—demonstrate notably positive value-weighted daily momentum profits. Only the U.K. presents significant positive equal-weighted daily momentum patterns. Notably, 16 of these developed markets display pronounced value-weighted daily reversal effects, and this number rises to 19 when considering equal-weighted daily reversals. Such daily reversal phenomenon is consistent with the bid-ask bounce effect.

Even though we lack access to granular trading data and investor identity in international markets, we expect to observe asymmetric effects in other markets that exhibit daily momentum—assuming new investors exhibit heightened trading activities during bullish market conditions. As depicted in Table IX, most of these markets display asymmetric daily momentum, accentuating more prominently during bullish periods than in bearish ones. It remains consistent whether we employ value or equal weightings. Such findings echo the patterns discerned in the Chinese stock market.

In summary, the phenomenon of daily price momentum is evident across various markets, underscoring that it is not an exclusive attribute of the Chinese stock market. Notably, this momentum is more pronounced in emerging markets, with nearly half of our sampled emerging markets manifesting this phenomenon. In contrast, developed markets predominantly show tendencies of daily return reversals. Moreover, within the emerging markets that display price momentum, there's a consistent asymmetric pattern between bullish and bearish phases. This pattern alludes to the potential influence of new investors as a catalyst for driving daily momentum.

IV. Conclusion

In this paper, we present a new puzzle—daily price momentum in the Chinese stock market. Our international sample, including 21 emerging markets and 21 developed markets, shows that around half of emerging markets exhibit significant daily price momentum effects, while developed markets are more likely to display daily reversal patterns.

Using account-level data from the SZSE in China, we identify five groups of investors, including a group of new investors without any stock trading experience. By comparing the net buying of each investor group in response to stocks' past returns, we find that new investors and other retail investors with small accounts significantly contribute to daily price momentum and subsequent price reversal, while the other groups—large retail investors, mutual funds, and other institutions—counterbalance these price effects. The contribution from new investors is particularly 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

Exp: 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 1. 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.

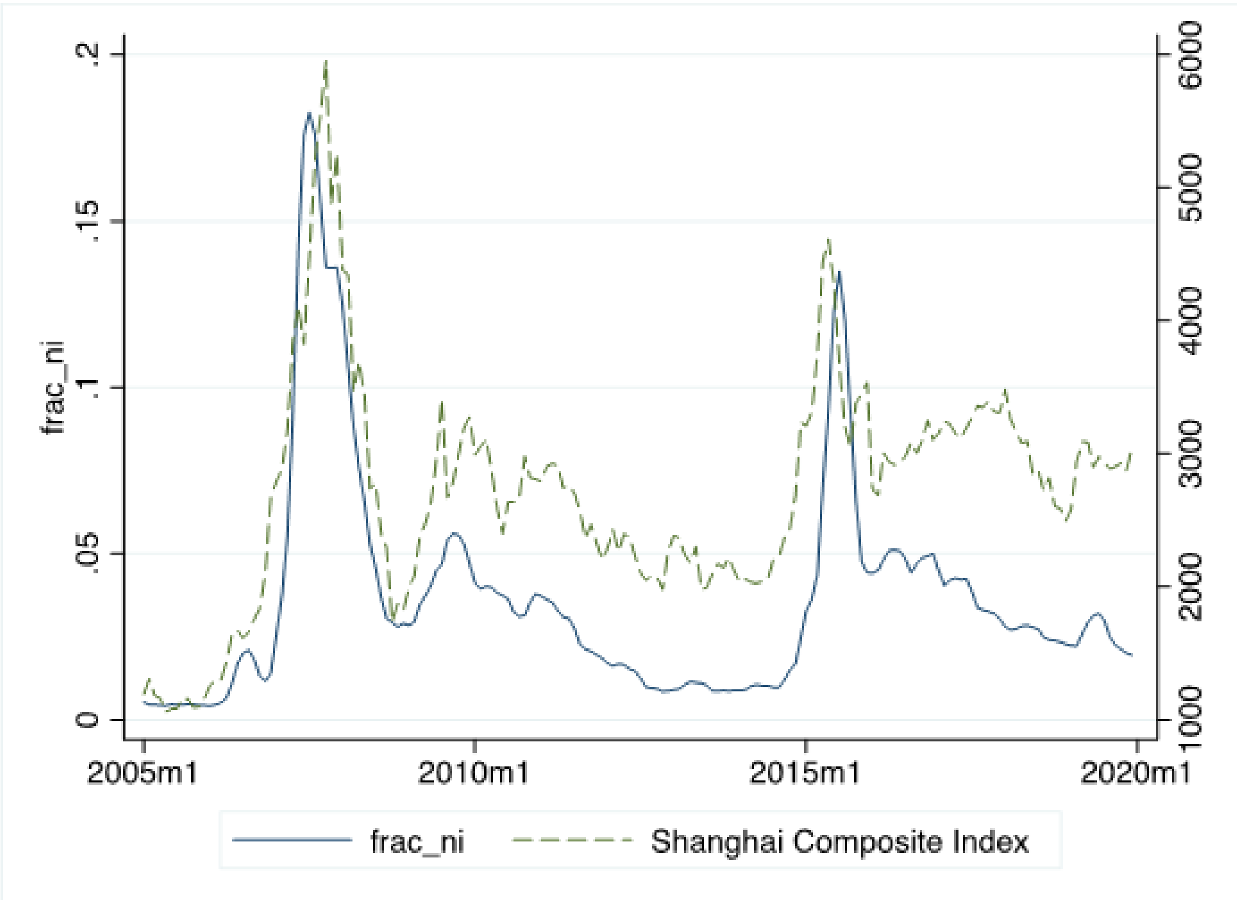

Figure 2. Fraction of Trading Volume

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, experienced retail account (*Exp*)—those with less than three million RMB, and large retail account (*L*)—those exceeding three million RMB, mutual fund (*MF*), other institutions (*OI*), and other investors (*Other*).

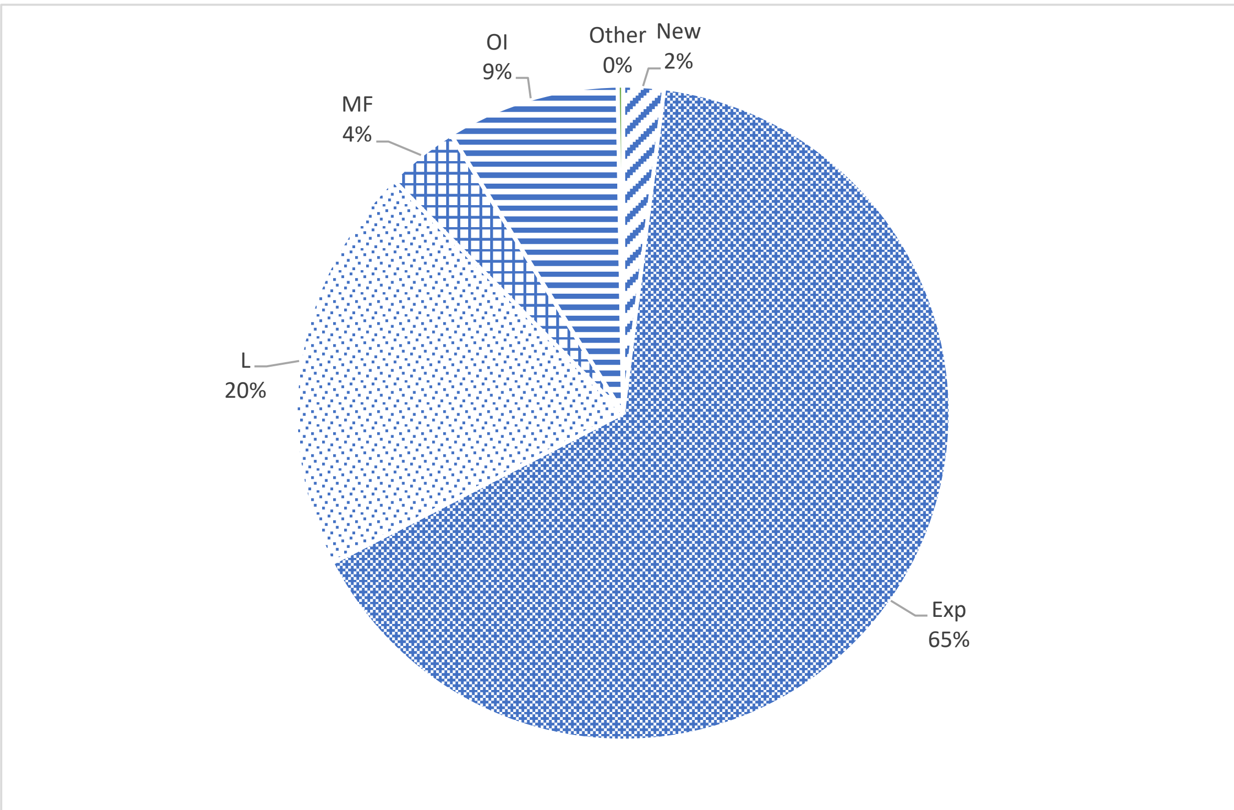

Table I. Price Reactions to Past Returns and Investor Trading

In this table, Panel A presents the results in the Fama-MacBeth regressions of the future 1-, 3-, and 6-month stock returns on the current month return as well as the past 11-month return. Panel B presents the results in the Fama-MacBeth regressions of the future 1-, 2-, and 3-week stock returns on the current week return as well as the previous 3-week return. Panel C presents the results in the Fama-MacBeth regressions of the future stock returns over 1-day, Days 2 to 6, and Days 2 to 11 on Day 0, over previous five days, from Days -21 to -6. t-statistics are reported in parentheses.

Panel A: Monthly

	Ret_{m+1}	$Ret_{m+1\to m+3}$	$Ret_{m+1\to m+6}$
	(1)	(2)	(3)
Ret_m	-0.026	-0.014	0.003
	(-2.68)	(-0.72)	(0.09)
$Ret_{m-11\to m-1}$	-0.000	-0.002	-0.008
	(-0.10)	(-0.13)	(-0.25)
Ln_cap	-0.003	-0.009	-0.017
	(-1.76)	(-1.87)	(-2.04)
Abn_turnover	-0.011	-0.015	-0.018
	(-3.70)	(-2.94)	(-2.14)
BM	0.008	0.019	0.037
	(2.65)	(2.17)	(2.05)
Vol	0.108	-0.395	-1.148
	(0.86)	(-1.61)	(-3.26)
Max	-0.095	-0.11	-0.089
	(-3.90)	(-3.15)	(-1.16)
Illiq	0.398	1.772	2.279
	(1.44)	(2.69)	(2.05)
Constant	0.061	0.191	0.393
	(2.20)	(2.35)	(2.47)
N	280700	280700	280700
R-sq	0.105	0.103	0.094

Panel B: Weekly

	Ret_{w+1}	$Ret_{w+1 \to w+2}$	$Ret_{w+1 \to w+3}$
	(1)	(2)	(3)
Ret_w	-0.092	-0.114	-0.123
	(-19.00)	(-17.20)	(-14.95)
$Ret_{w-3 \to w-1}$	-0.028	-0.042	-0.050
	(-9.88)	(-10.09)	(-9.27)
Ln_cap	-0.001	-0.002	-0.003
	(-3.13)	(-2.82)	(-2.56)
Abn_turnover	-0.008	-0.012	-0.015
	(-10.81)	(-11.87)	(-10.78)
BM	0.006	0.010	0.012
	(6.12)	(5.55)	(4.91)
Vol	-0.296	-0.658	-1.001
	(-2.95)	(-3.97)	(-4.84)
Max	0.511	0.834	1.022
	(26.18)	(25.10)	(23.97)
Illiq	0.081	0.218	0.338
	(0.71)	(1.07)	(1.25)
Constant	0.006	0.016	0.031
	(1.19)	(1.52)	(1.86)
N	1444919	1444919	1444919
R-sq	0.162	0.183	0.184

Panel C: Daily

	Ret_{d+1}	$Ret_{d+2\to d+6}$	$Ret_{d+2\to d+11}$
	(1)	(2)	(3)
Ret_d	0.02708	-0.12812	-0.14193
	(7.54)	(-21.09)	(-17.54)
$Ret_{d-5\to d-1}$	-0.02764	-0.06886	-0.08803
	(-24.92)	(-20.76)	(-17.20)
$Ret_{d-21\to d-6}$	-0.00903	-0.03257	-0.04928
	(-17.73)	(-15.04)	(-13.56)
Ln_cap	-0.00026	-0.00109	-0.00195
	(-3.59)	(-3.13)	(-2.90)
Abn_turnover	-0.00199	-0.00420	-0.00625
	(-15.23)	(-14.90)	(-15.39)
BM	0.00143	0.00519	0.00823
	(7.03)	(5.77)	(5.00)
Vol	-0.07058	-0.39324	-0.79139
	(-3.43)	(-4.56)	(-5.67)
Max	0.12614	0.50647	0.81620
	(28.49)	(26.28)	(25.47)
Illiq	0.05424	0.28925	0.56356
	(1.42)	(1.85)	(2.17)
Constant	0.00132	0.00551	0.01623
	(1.18)	(0.98)	(1.46)
N	5896299	5896299	5896299
R-sq	0.132	0.166	0.185

Table II. 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	0.0021	0.0007	0.0004	0.0001	-0.0015	-0.0010
	(7.06)	(1.98)	(0.94)	(0.32)	(-3.07)	(-1.77)
2d	0.0003	-0.0011	-0.0015	-0.0029	-0.0044	-0.0032
	(1.24)	(-2.85)	(-3.40)	(-5.57)	(-7.65)	(-4.38)
3d	-0.0001	-0.0014	-0.0029	-0.0044	-0.0055	-0.0038
	(-0.67)	(-4.08)	(-6.29)	(-7.91)	(-8.90)	(-4.41)
5d	-0.0012	-0.0031	-0.0045	-0.0054	-0.0060	-0.0043
	(-5.98)	(-8.76)	(-9.25)	(-9.12)	(-8.75)	(-3.94)
10d	-0.0006	-0.0017	-0.0022	-0.0026	-0.0029	-0.0009
	(-3.31)	(-4.49)	(-4.02)	(-3.79)	(-3.46)	(-0.62)
	Equal-weight					
	1d	2d	3d	4d	5d	10d
J:Sorting return horizon						
1d	0.0015	-0.0000	-0.0002	-0.0003	-0.0020	-0.0012
	(5.40)	(-0.03)	(-0.42)	(-0.72)	(-4.75)	(-2.61)
2d	-0.0006	-0.0023	-0.0029	-0.0044	-0.0060	-0.0046
	(-3.22)	(-7.58)	(-8.00)	(-10.93)	(-13.16)	(-8.53)
3d	-0.0010	-0.0027	-0.0045	-0.0062	-0.0074	-0.0058
	(-5.83)	(-9.91)	(-12.48)	(-14.35)	(-15.02)	(-9.18)
5d	-0.0020	-0.0046	-0.0061	-0.0072	-0.0079	-0.0066
	(-12.89)	(-16.05)	(-15.79)	(-15.47)	(-14.76)	(-8.44)
10d	-0.0013	-0.0029	-0.0037	-0.0044	-0.0049	-0.0042
	(-9.55)	(-10.78)	(-9.65)	(-8.92)	(-8.22)	(-4.26)

Table III. 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.

Panel A: Age and Gender

	Age		Male Ratio	
Year	New	Retail	New	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

Invclss	New(<300)	Exp(<300)	L(>300)	MF	OI
Turnover	18.12%	8.03%	3.26%	1.98%	1.66%

Table IV. 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)				
$Netbuy(Exp)_m$		-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 V. 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. *t*-statistics are reported in parentheses.

	$Netbuy(New)_{d+1}$	$Netbuy(Exp)_{d+1}$	$Netbuy(L)_{d+1}$	$Netbuy(MF)_{d+1}$	$Netbuy(OI)_{d+1}$
	(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

Table VI. 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. t-statistics are reported in parentheses.

Panel A

	Ret_{d+1}	$Ret_{d+2\to d+6}$	$Ret_{d+2\to d+11}$
	(1)	(2)	(3)
Ret_d	0.02760	-0.03760	-0.00023
	(6.05)	(-6.10)	(-0.03)
$Ret_{d-5\to d-1}$	-0.01601	-0.01486	-0.00692
	(-14.67)	(-3.77)	(-1.02)
$Ret_{d-21\to d-6}$	-0.00085	-0.00807	-0.01737
	(-1.54)	(-3.10)	(-3.82)
Ln_cap	-0.00051	-0.00180	-0.00317
	(-5.48)	(-3.98)	(-3.76)
Turnover_float	-0.04427	-0.13587	-0.23637
	(-14.84)	(-12.88)	(-13.12)
BM	0.00027	0.00154	0.00251
	(1.14)	(1.32)	(1.15)
$Netbuy(New)_{d+1}$	-0.00718	-0.00226	-0.00272
	(-12.57)	(-8.20)	(-7.81)
$Ret_d * Netbuy(New)_{d+1}$	0.13504	-0.03950	-0.07682
	(17.35)	(-5.51)	(-8.36)
Constant	0.00937	0.03084	0.05562
	(5.89)	(4.02)	(3.89)
N	2402764	2402764	2402764
R-sq	0.126	0.102	0.108

Panel B

	Ret_{d+1}	$Ret_{d+2\to d+6}$	$Ret_{d+2\to d+11}$
	(1)	(2)	(3)
Ret_d	0.03274	-0.05185	-0.02265
	(6.77)	(-8.49)	(-2.89)
$Ret_{d-5\to d-1}$	-0.02744	-0.01862	-0.01214
	(-20.98)	(-4.84)	(-1.84)
$Ret_{d-21\to d-6}$	-0.00246	-0.00849	-0.01805
	(-4.59)	(-3.28)	(-4.00)
Ln_cap	-0.00001	-0.00172	-0.00308
	(-0.11)	(-3.85)	(-3.66)
Turnover_float	-0.01478	-0.13144	-0.23363
	(-4.93)	(-12.44)	(-13.00)
BM	0.00032	0.00157	0.00260
	(1.49)	(1.36)	(1.19)
$Netbuy(Exp)_{d+1}$	-0.00248	-0.00067	-0.00083
	(-43.67)	(-14.60)	(-14.53)
$Ret_d * Netbuy(Exp)_{d+1}$	0.01028	-0.00451	-0.00556
	(17.87)	(-6.04)	(-5.95)
Constant	0.00022	0.02948	0.05398
	(0.16)	(3.86)	(3.78)
N	2402764	2402764	2402764
R-sq	0.252	0.105	0.111

Panel C

	Ret_{d+1}	$Ret_{d+2\to d+6}$	$Ret_{d+2\to d+11}$
	(1)	(2)	(3)
Ret_d	0.05646	-0.04544	-0.01384
	(13.16)	(-7.69)	(-1.70)
$Ret_{d-5\to d-1}$	-0.01511	-0.01585	-0.00813
	(-13.91)	(-4.01)	(-1.20)
$Ret_{d-21\to d-6}$	-0.00012	-0.00784	-0.01726
	(-0.23)	(-3.02)	(-3.81)
Ln_cap	-0.00034	-0.00175	-0.00311
	(-3.85)	(-3.89)	(-3.69)
Turnover_float	-0.03896	-0.13704	-0.24010
	(-14.00)	(-12.83)	(-13.24)
BM	0.00016	0.00136	0.00238
	(0.67)	(1.16)	(1.08)
$Netbuy(Large)_{d+1}$	0.00168	0.00049	0.00064
	(36.23)	(10.99)	(9.57)
$Ret_d * Netbuy(Large)_{d+1}$	-0.00670	0.00479	0.00717
	(-9.62)	(3.24)	(4.50)
Constant	0.00583	0.03011	0.05469
	(3.95)	(3.93)	(3.83)
N	2402764	2402764	2402764
R-sq	0.153	0.103	0.100

Panel D

	Ret_{d+1}	$Ret_{d+2\to d+6}$	$Ret_{d+2\to d+11}$
	(1)	(2)	(3)
Ret_d	0.02165	-0.06135	-0.03481
	(5.19)	(-10.48)	(-4.49)
$Ret_{d-5\to d-1}$	-0.02236	-0.01761	-0.01084
	(-18.70)	(-4.47)	(-1.62)
$Ret_{d-21\to d-6}$	-0.00252	-0.00871	-0.01821
	(-4.73)	(-3.38)	(-4.05)
Ln_cap	-0.00044	-0.00184	-0.00322
	(-4.79)	(-4.07)	(-3.82)
Turnover_float	-0.03861	-0.14135	-0.24574
	(-14.47)	(-13.39)	(-13.63)
BM	0.00044	0.00155	0.00265
	(1.88)	(1.35)	(1.22)
$Netbuy(MF)_{d+1}$	0.00257	0.00082	0.00114
	(26.18)	(9.03)	(7.20)
$Ret_d * Netbuy(MF)_{d+1}$	-0.00949	0.01253	0.01896
	(-9.22)	(7.27)	(8.11)
Constant	0.00765	0.03141	0.05644
	(4.87)	(4.09)	(3.94)
N	2402764	2402764	2402764
R-sq	0.142	0.102	0.108

Panel E

	Ret_{d+1}	$Ret_{d+2\to d+6}$	$Ret_{d+2\to d+11}$
	(1)	(2)	(3)
Ret_d	0.04320	-0.05279	-0.02443
	(10.87)	(-8.73)	(-3.02)
$Ret_{d-5\to d-1}$	-0.01628	-0.01604	-0.00887
	(-14.50)	(-4.05)	(-1.31)
$Ret_{d-21\to d-6}$	-0.00078	-0.00805	-0.01746
	(-1.43)	(-3.09)	(-3.85)
Ln_cap	-0.00045	-0.00179	-0.00316
	(-4.92)	(-3.95)	(-3.73)
Turnover_float	-0.04263	-0.14060	-0.24451
	(-15.36)	(-13.13)	(-13.46)
BM	0.00043	0.00150	0.00254
	(1.78)	(1.30)	(1.16)
$Netbuy(OI)_{d+1}$	0.00135	0.00043	0.00064
	(24.14)	(6.92)	(7.52)
$Ret_d * Netbuy(OI)_{d+1}$	-0.00882	0.00504	0.00704
	(-9.66)	(3.28)	(3.17)
Constant	0.00781	0.03087	0.05563
	(5.06)	(4.00)	(3.87)
N	2402764	2402764	2402764
R-sq	0.128	0.101	0.108

Panel F

	Ret_{d+1}	$Ret_{d+2\to d+6}$	$Ret_{d+2\to d+11}$
	(1)	(2)	(3)
Ret_d	-0.00489	-0.04531	-0.01049
	(-0.99)	(-6.85)	(-1.31)
$Ret_{d-5\to d-1}$	-0.03002	-0.01785	-0.01071
	(-23.89)	(-4.61)	(-1.63)
$Ret_{d-21\to d-6}$	-0.00281	-0.00845	-0.01769
	(-5.30)	(-3.30)	(-3.96)
Ln_cap	-0.00005	-0.00177	-0.00313
	(-0.57)	(-4.00)	(-3.75)
Turnover_float	-0.02763	-0.13415	-0.23710
	(-9.20)	(-12.63)	(-13.07)
BM	0.00034	0.00159	0.00269
	(1.58)	(1.39)	(1.24)
$Netbuy(New)_{d+1}$	-0.00066	-0.00079	-0.00122
	(-2.30)	(-3.32)	(-3.83)
$Ret_d * Netbuy(New)_{d+1}$	0.16582	-0.01698	-0.04744
	(17.50)	(-2.52)	(-5.31)
$Netbuy(Exp)_{d+1}$	-0.00211	-0.00062	-0.00077
	(-30.00)	(-9.22)	(-9.82)
$Ret_d * Netbuy(Exp)_{d+1}$	0.00446	-0.00465	-0.00474
	(5.17)	(-3.20)	(-2.59)
$Netbuy(Large)_{d+1}$	0.00043	0.00009	0.00008
	(7.55)	(1.19)	(0.97)
$Ret_d * Netbuy(Large)_{d+1}$	-0.00215	0.00046	0.00082
	(-2.35)	(0.27)	(0.43)
$Netbuy(MF)_{d+1}$	0.00105	0.00030	0.00043
	(14.40)	(3.50)	(2.69)
$Ret_d * Netbuy(MF)_{d+1}$	-0.00095	0.00807	0.01239
	(-0.86)	(3.66)	(4.43)
Constant	0.00109	0.03008	0.05456
	(0.80)	(3.97)	(3.84)
N	2402764	2402764	2402764
R-sq	0.301	0.128	0.132

Table VII. Market Up and Down

This table reports return continuation patterns (columns 1 and 2), new investor reactions to daily returns (columns 3 and 4), and price responses to past returns and investor trading (columns 5 and 6), when market returns are above the median ("Market-up") and below the median ("Market-down"). t-statistics are reported in parentheses.

Dependent Variable:	Ret_{d+1}		$Netbuy(New)_{d+1}$		Ret_{d+1}	
	Market-up	Market-down	Market-up	Market-down	Market-up	Market-down
	(1)	(2)	(3)	(4)	(5)	(6)
Ret_d	0.06957	0.03112	3.64145	1.79886	0.04006	0.01515
	(12.64)	(6.63)	(7.03)	(12.41)	(6.42)	(2.52)
$Ret_{d-5\to d-1}$	-0.01816	-0.00742	0.24206	-0.01236	-0.02169	-0.01033
	(-13.46)	(-5.29)	(2.79)	(-0.47)	(-15.62)	(-6.77)
$Ret_{d-21\to d-6}$	-0.00154	0.00065	0.03811	-0.04945	-0.00208	0.00038
	(-1.98)	(0.89)	(1.44)	(-4.70)	(-2.72)	(0.50)
Ln_cap	-0.00066	-0.00028	-0.00355	-0.00029	-0.00068	-0.00035
	(-5.23)	(-2.72)	(-1.33)	(-0.20)	(-5.13)	(-3.34)
Turnover_float	-0.03687	-0.03765	3.48388	1.50370	-0.04048	-0.04806
	(-11.27)	(-12.55)	(8.38)	(9.93)	(-9.12)	(-11.79)
BM	-0.00084	0.00126	-0.00001	-0.00085	-0.00087	0.00142
	(-2.70)	(3.53)	(-0.00)	(-0.16)	(-2.58)	(3.63)
$Netbuy(New)_{d+1}$					-0.00785	-0.00650
					(-10.08)	(-8.17)
$Ret_d * Netbuy(New)_{d+1}$					0.14407	0.12601
					(12.49)	(11.83)
Constant	0.01157	0.00472	-0.00064	0.05180	0.01249	0.00625
	(5.63)	(2.70)	(-0.01)	(2.33)	(5.77)	(3.49)
N	1363327	1419546	1170077	1232687	1170077	1232687
R-sq	0.083	0.085	0.089	0.069	0.125	0.126

Table VIII. Daily Momentum or Reversal in International Markets

This table presents the daily momentum or reversal in major markets (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.

Emerging Markets	Value Weighted	Equal Weighted	Developed Markets	Value Weighted	Equal Weighted
Brazil	-0.0016	-0.0058	Austria	0.0020	-0.0001
	(-5.86)	(-23.47)		(5.96)	(-0.36)
Chile	0.0031	0.0042	Australia	-0.0034	-0.0211
	(12.70)	(17.54)		(-15.40)	(-46.39)
China	0.0013	0.0011	Belgium	-0.0019	-0.0042
	(6.64)	(5.74)		(-11.49)	(-22.87)
Czech Republic	0.0156	0.0282	Canada	-0.0159	-0.0610
	(10.40)	(16.14)		(-18.96)	(-38.97)
Egypt	0.0079	0.0087	Denmark	-0.0005	-0.0070
	(18.14)	(19.63)		(-2.32)	(-21.24)
Greece	0.0029	0.0002	Finland	-0.0027	-0.0089
	(6.44)	(0.28)		(-12.22)	(-37.73)
India	-0.0001	-0.0048	France	-0.0005	-0.0032
	(-0.11)	(-5.51)		(-3.60)	(-17.01)
Indonesia	-0.0084	-0.0167	Germany	-0.0010	-0.0067
	(-9.61)	(-17.12)		(-5.49)	(-18.01)
Israel	0.0060	0.0065	Hong Kong	-0.0001	-0.0052
	(16.09)	(16.36)		(-0.29)	(-15.40)
Malaysia	-0.0050	-0.0144	Italy	-0.0003	-0.0031
	(-20.72)	(-24.82)		(-2.00)	(-20.89)
Mexico	0.0043	0.0047	Japan	-0.0017	-0.0041
	(8.43)	(8.96)		(-11.38)	(-30.72)
Pakistan	0.0029	-0.0055	Netherlands	0.0005	-0.0017
	(6.27)	(-9.29)		(2.76)	(-9.03)
Philippines	-0.0049	-0.0122	New Zealand	-0.0013	-0.0060
	(-11.82)	(-32.34)		(-6.04)	(-26.27)
Poland	-0.0016	-0.0096	Norway	-0.0024	-0.0070
	(-5.72)	(-21.60)		(-10.68)	(-23.36)
Saudi Arabia	0.0016	0.0013	Portugal	-0.0021	-0.0048
	(6.56)	(7.06)		(-3.00)	(-7.99)
South Africa	0.0014	-0.0082	Singapore	-0.0069	-0.0219
	(4.06)	(-14.71)		(-21.54)	(-24.67)
South Korea	0.0033	0.0025	Spain	0.0002	-0.0020
	(10.69)	(8.23)		(1.36)	(-12.02)
Taiwan	0.0018	0.0032	Sweden	-0.0018	-0.0096
	(6.76)	(11.03)		(-8.86)	(-29.41)
Thailand	-0.0009	-0.0056	Switzerland	-0.0007	-0.0049
	(-2.73)	(-12.20)		(-5.04)	(-35.93)
Turkey	0.0018	0.0007	UK	0.0020	0.0059
	(4.47)	(1.77)		(11.07)	(16.31)
Vietnam	0.0032	-0.0043	USA	-0.0015	-0.0189
	(4.93)	(-5.84)		(-7.76)	(-30.64)

Table IX. 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 ("Marker-up") and below the median ("market-down"). t-statistics are reported in parentheses.

	Value-weight		Equal-weight	
	Market-up	Market-down	Market-up	Market-down
Austria	0.0021	0.0019	0.0005	-0.0008
	(4.60)	(4.24)	(1.17)	(-1.62)
Chile	0.0038	0.0023	0.0051	0.0034
	(10.79)	(7.82)	(14.95)	(11.03)
China	0.0018	0.0008	0.0016	0.0005
	(5.92)	(3.28)	(5.71)	(2.04)
Czech Republic	0.0149	0.0164	0.0272	0.0292
	(6.29)	(9.02)	(10.35)	(13.79)
Egypt	0.0091	0.0066	0.0097	0.0077
	(15.60)	(11.75)	(16.35)	(13.18)
Greece	0.0038	0.0021	0.0018	-0.0015
	(5.26)	(3.90)	(2.15)	(-2.29)
Israel	0.0073	0.0047	0.0081	0.0048
	(13.10)	(10.38)	(14.20)	(9.88)
Mexico	0.0055	0.0032	0.0063	0.0031
	(6.69)	(5.36)	(8.65)	(4.94)
Netherlands	0.0009	0.0001	-0.001	-0.0024
	(3.46)	(0.54)	(-3.61)	(-9.93)
Pakistan	0.0041	0.0016	-0.0045	-0.0066
	(6.41)	(2.65)	(-5.09)	(-8.61)
Saudi Arabia	0.0024	0.0008	0.0017	0.001
	(7.31)	(2.31)	(6.60)	(3.77)
South Africa	0.0020	0.0007	-0.0072	-0.0092
	(3.86)	(1.81)	(-8.84)	(-12.80)
South Korea	0.0046	0.0020	0.0039	0.0012
	(10.01)	(5.31)	(8.34)	(3.37)
Spain	0.0005	0.0000	-0.0015	-0.0024
	(2.06)	(-0.22)	(-6.37)	(-11.67)
Taiwan	0.0021	0.0015	0.0038	0.0025
	(5.73)	(4.01)	(8.99)	(6.52)
Turkey	0.0035	0.0001	0.0021	-0.0008
	(5.40)	(0.24)	(3.70)	(-1.83)
UK	0.0020	0.0019	0.0065	0.0054
	(7.93)	(7.64)	(12.84)	(10.54)
Vietnam	0.0046	0.0019	-0.003	-0.0056
	(4.67)	(2.47)	(-2.78)	(-6.60)

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

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

Table A1. 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 A2. 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 A3. 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
$Netbuy(Exp)_m$	-1.84592	30.58776	-10.47359	-0.44758	8.80716	108303
$Netbuy(Large)_m$	-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
$Netbuy(Large)_d$	-0.01954	3.04808	-0.78896	0.00530	0.79336	2418806
$Netbuy(Exp)_d$	-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 A4. 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 A5. 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+1}				
	(1)	(2)	(3)	(4)	(5)
$Netbuy(New)_m$	-0.00347				
	(-5.80)				
$Netbuy(Exp)_m$		-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

Panel B:	Ret_{m+3}				
	(1)	(2)	(3)	(4)	(5)
$Netbuy(New)_m$	-0.00543				
	(-5.46)				
$Netbuy(Exp)_m$		-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)
$Ret_{m-11\to m-1}$	-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 C:	Ret_{m+6}				
	(1)	(2)	(3)	(4)	(5)
$Netbuy(New)_m$	-0.00823				
	(-6.13)				
$Netbuy(Exp)_m$		-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 D:	Ret_{m+12}				
	(1)	(2)	(3)	(4)	(5)
$Netbuy(New)_m$	-0.01073				
	(-5.11)				
$Netbuy(Exp)_m$		-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)
$Ret_{m-11 \to m-1}$	-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 E:	Ret_dgtw_{m+1}				
	(1)	(2)	(3)	(4)	(5)
$Netbuy(New)_m$	-0.00306				
	(-5.39)				
$Netbuy(Exp)_m$		-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)
$Ret_{m-11 \to m-1}$	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 F:	Ret_dgtw_{m+3}				
	(1)	(2)	(3)	(4)	(5)
$Netbuy(New)_m$	-0.00497				
	(-4.75)				
$Netbuy(Exp)_m$		-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)
$Ret_{m-11 \rightarrow m-1}$	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 G:			Ret_dgtw_{m+6}		
	(1)	(2)	(3)	(4)	(5)
$Netbuy(New)_m$	-0.00754				
	(-5.39)				
$Netbuy(Exp)_m$		-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 H:	Ret_dgtw_{m+12}				
	(1)	(2)	(3)	(4)	(5)
$Netbuy(New)_m$	-0.00929				
	(-5.13)				
$Netbuy(Exp)_m$		-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 A6. 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 A7. 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)
$Netbuy(Exp)_d$	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 A8. 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