

Retail Trading and the Disappearance of Stock Return Predictability

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ABSTRACT

We examine the predictability of retail order flow using a novel database. Retail order flow predicts stock returns for up to five weeks during 2014–2016, but this predictability disappears in the subsequent 2017–2022 period. The early-period predictability is concentrated in small, low-liquidity stocks and during episodes of strong retail buying pressure. As market liquidity improves, the price impact and persistence of retail-driven demand imbalances diminish, weakening return predictability. These findings are more consistent with a friction-based explanation than with superior retail information. Regulatory changes, such as the 2016 Tick Size Pilot Program, further contribute to the short-term decline.

Keywords: Retail trading, Predictability, Common Factors, Liquidity

JEL Classification: G12 G17

The authors thank Adelphe Ekponon, Kaitao Lin (discussant), Jeff Pontiff, Qianru Qi and conference and seminar participants at the Telfer School of Management and 2025 European Financial Management Annual Meeting for helpful comments and suggestions.

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ABSTRACT

We examine the predictability of retail order flow using a novel database. Retail order flow predicts stock returns for up to five weeks during 2014–2016, but this predictability disappears in the subsequent 2017–2022 period. The early-period predictability is concentrated in small, low-liquidity stocks and during episodes of strong retail buying pressure. As market liquidity improves, the price impact and persistence of retail-driven demand imbalances diminish, weakening return predictability. These findings are more consistent with a friction-based explanation than with superior retail information. Regulatory changes, such as the 2016 Tick Size Pilot Program, further contribute to the short-term decline.

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1. Introduction.

Over the last decade, retail participation in stock markets has increased dramatically, driven by factors such as increased savings (Li et al., 2020), easier coordination facilitated by social media (e.g., Cookson et al., 2022; Hu et al., 2021), convenient access through mobile devices, and the rise of commission-free fintech trading apps (Ozik et al., 2021).¹ This trend was particularly pronounced during the COVID-19 pandemic, when stay-at-home orders and federal stimulus checks boosted households' participation in stock trading. The daily net flows of US retail investors rose from \$620 million in 2014 to \$1.32 billion in 2022, and they poured a record of \$1.51 billion into the stock market after the Q1 2023 earnings season.² By 2021, retail investors accounted for about 25% of total equity trading volume, nearly double the share observed a decade earlier.³ According to Scott Rubner, head of equity and equity derivatives strategy at Citadel Securities, retail investors are “now a price-setter, a dominant force in the market”.⁴ In light of this growing influence, a central question is whether retail trades merely exert temporary price pressure or instead predict future stock returns by reflecting information about firm fundamentals.

Whether retail trading predicts stock returns is crucial for several reasons: for other market participants to refine their trading strategies and risk management practices; for behavioral finance researchers to analyze retail investor psychology and trading behavior; for improving our understanding of market efficiency; and for policymakers seeking to monitor and regulate the stock market. Despite its importance, the academic literature reaches mixed conclusions regarding the

¹ To compete with fintech trading apps like Robinhood, which provide zero-commission trading, legacy brokerage firms, such as Charles Schwab, Fidelity, TD Ameritrade, and E-Trade, started to offer low commissions and integrated one-stop-shop financial services into smartphone accessible apps.

² For more details, see <https://www.visualcapitalist.com/charted-u-s-retail-investor-inflows-2014-2023>

³ For more details, see https://irlaw.umkc.edu/faculty_works/928

⁴ For more details, see <https://www.wsj.com/finance/stocks/everyday-traders-go-from-fringe-players-to-dominant-market-force-51edb01b>

informativeness of retail trading. Barber and Odean (2000, 2008) characterize retail investors as uninformed, inexperienced in stock selection, and prone to behavioral biases. In contrast, a growing body of later research finds that retail trading can predict stock returns under certain conditions. Kaniel et al. (2008, 2012) document that retail investors tend to act as liquidity providers. Kelly and Tetlock (2013) show that retail order flows respond to fundamental news and contain information about future earnings announcements. More recently, Boehmer, Jones, Zhang, and Zhang (BJZZ, 2021) introduce a novel methodology to identify marketable retail trades using fractional-penny executions from the TAQ dataset. They find strong and persistent return predictability, showing that retail flow imbalance forecasts stock returns for up to eight weeks during the 2010-2015 period. They also suggest that retail investors may be informed and possess firm-level information that is not yet incorporated into prices.

Motivated by the dramatic expansion in retail participation and the ongoing debate over its informativeness, this paper reassesses whether retail order flow predicts stock returns over an extended and more recent sample period from 2014 to 2022, relative to BJZZ. In light of recent discussions on retail trade classification (Barber et al. 2023), we employ a novel dataset of retail trading activity.⁵ We document a pronounced decline in the return predictability of retail order flow over time, with significant predictability in the early part of the sample that dissipates in more recent years. We further identify economic mechanisms underlying both the initial predictability and its subsequent erosion, highlighting the role of market liquidity, particularly among small stocks, as a key channel driving these dynamics.

⁵ Barber et al. (2023) raise concerns about potential classification error in identifying retail trades, although the BJZZ methodology remains widely used in the literature.

We begin by reassessing the return predictability of retail equity trading over the 2014-2022 period. Our analysis relies on daily US stock-level retail flow data from VandaTrack, which incorporates proprietary adjustments designed to improve the precision of retail volume estimation.⁶ Similar to the prior literature (e.g., BJZZ; Barber et al., 2024), we measure retail trading activity using retail flow imbalance, a measure of net retail trading pressure. Using Fama-MacBeth regressions, we find that during the 2014-2016 period, consistent with BJZZ, retail flow imbalance significantly predicts future weekly stock returns, with predictive power persisting for up to five weeks. However, this predictability disappears entirely in the subsequent 2017-2022 period. These results are confirmed using a portfolio analysis designed to exploit the predictability.

We next investigate the sources of the decline in retail trading predictability. Using piecewise linear regressions (Sirri and Tufano, 1998), we show that during 2014-2016, predictive power is concentrated in the top quartile of retail flow imbalance, suggesting that stocks with the strongest net retail buying earn higher subsequent returns. In contrast, during 2017-2022, the top quartile no longer exhibits significant predictive ability. This pattern suggests that the early-period predictability may have been driven by persistent retail demand pressure or informational content in retail trades—mechanisms that appear to weaken in the later sample.

To assess whether the observed predictability reflects systematic factor exposure, we replace raw returns with DGTW characteristics-adjusted returns (Danel, Grinblatt, Titman, and Wermers, 1997), which control for size, book-to-market, and momentum. We find that both the

⁶ VandaTrack data is a proprietary data platform developed by Vanda Research that provides daily data of retail purchases and sales for individual US-listed stocks and ETFs. The dataset is designed to meet the needs of professional investors, financial research firms, and more recently, academic researchers seeking to systematically track retail activity. VandaTrack data are available beginning in 2014. Hence, our sample period begins in 2014, rather than 2010 as in BJZZ. Empirical comparisons indicate that the VandaTrack measure exhibits lower measurement noise and contains incremental predictive information beyond that captured by the BJZZ proxy. A detailed comparison of the two retail trading datasets is provided in the Internet Appendix.

economic magnitude and statistical significance of the top-quartile effect are substantially attenuated, indicating that the 2014-2016 predictability largely reflects retail investors' systematic tilts toward these factors. Examining firm size, we find that the positive predictive power is driven entirely by small-cap stocks in 2014-2016 and vanishes during 2017-2022, indicating that the decline is concentrated among small stocks.⁷

Taken together, these findings point to a friction-based explanation: retail predictability is concentrated in segments of the market with limited liquidity and slow absorption of order flow imbalances. We therefore examine whether changes in market liquidity can account for both the emergence and disappearance of retail trading predictability. Small stocks experienced substantial increases in both retail and institutional trading in the later period, contributing to a significant improvement in liquidity. The Amihud (2002) illiquidity measure shows that average weekly illiquidity among small stocks declines from 80.11 in 2014-2016 to 34.06 in 2017-2022. A decomposition of the predictability reveals that it is driven primarily by persistent retail demand shocks, rather than informational content. Improved liquidity should reduce the price impact of retail-induced demand imbalances, weakening the predictability. Consistent with this mechanism, during 2014-2016, the top quartile of retail flow imbalance predicts returns only among small stocks with low liquidity, but not among high-liquidity small stocks. These findings indicate that liquidity plays a key role in explaining retail trading predictability in the early period and its subsequent erosion.

To isolate the roles of size and liquidity, we construct an indicator identifying small stocks with low liquidity. Once these small, low-liquidity stocks are excluded, retail flow imbalance loses

⁷ We find retail investors' persistent predictability for value stocks over the next five weeks, but it does not have significant change from 2014 to 2022. Therefore, exposure to value stocks could not explain the decline in predictability. We also find no evidence that exposure to momentum, investment, or profitability factors contribute to the predictability or its evolution.

all predictive power even during 2014 – 2016. Portfolio-level evidence yields consistent results. These findings indicate that, beyond small and illiquid stocks, retail trading does not generate meaningful return predictability in the earlier period, consistent with the absence of predictability during 2017-2022. A vector autoregressive (VAR) analysis further supports this mechanism by showing that Granger causality runs from stock illiquidity to retail-based returns.

To further assess whether liquidity drives retail trading predictability, we examine whether improvements in market depth attenuate the predictive effects. If low liquidity is a key channel, predictability during 2014-2016 should be stronger among small stocks with limited participation by sophisticated investors such as transient institutional investors and short sellers, who can enhance market depth and accelerate the absorption of retail-induced demand imbalances. Our results are consistent with this hypothesis. We also provide complementary evidence based on variation in liquidity around Russell index reconstitution, consistent with the role of liquidity in shaping retail trading predictability. Consistent with changes in liquidity affecting the speed of demand absorption and hence predictability, retail flow imbalance loses (regains) predictive power following index inclusion (exclusion) for stocks initially outside (inside) the index.

Finally, we examine several alternative mechanisms that could potentially explain the decline in retail trading predictability. First, we study the 2016 Tick Size Pilot Program (TSPP), which altered trading conditions for a subset of small-cap stocks. We find that retail trading volume declines sharply among treated stocks relative to controls and this reduction in retail participation weakens retail-driven demand shocks and reduces return predictability, whereas predictability remains in the control group.⁸ This effect is distinct from the liquidity channel, as we find no

⁸ The remaining stocks are dominated by mid- and large-cap stocks which do not exhibit predictability in the sample period.

corresponding decline in liquidity for treated stocks. These results suggest that the TSPP contributed to the short-term decline in predictability from 2016 to 2017 by reducing retail participation.

Second, we assess the role of social media, given the growth of online discussion platforms and their influence on retail trading, highlighted by the 2021 GameStop episode. We find that, during 2014-2016, social media activity amplifies retail trading intensity and generates short-term demand shocks that affect next-week returns. However, this effect operates primarily in low-liquidity environments, suggesting that social media is not acting as an independent source of predictability.

Third, we test whether changes in the determinants of retail trading can explain the decline and find no evidence of systematic shifts in trading autocorrelation or preferences. Fourth, using VAR models, we find no evidence that macroeconomic conditions predict retail-based returns. Finally, analyses of two major retail flow shocks in 2018 and 2020 provide no evidence that the decline in predictability reflects a deterioration in the informational content of retail trading.⁹

Early studies (Odean 1999 and Barber and Odean 2000, 2002) using client-level data from US discount retail brokers document that retail investors exhibit behavioral biases and, on average, underperform. Consistent with this view, subsequent studies (e.g., Kumar and Lee, 2006; Dorn et al., 2008) find that retail order flow is largely uninformed with respect to future stock returns. In contrast, more recent studies using transaction-level account-type identifiers, such as NYSE audit trail data (Kaniel et al., 2012), US wholesaler order flow (Kelly and Tetlock, 2013), sub-penny executions (BJZZ), and proprietary customer classifications (Barrot et al., 2016), find that retail

⁹ These findings also strengthen the causal interpretation linking improved liquidity to the decline in predictability. Specifically, we find no evidence supporting the reverse causal channel in which an influx of inexperienced retail investors simultaneously reduces return predictability and improves liquidity.

trading activity can predict future stock returns.¹⁰

Our paper builds on BJZZ and contributes to the literature on retail trading and return predictability in three ways. First, we employ a novel retail trading database, VandaTrack, which exhibits lower measurement error and contains predictive variation not subsumed by BJZZ data. Second, we extend the sample through 2022, allowing us to examine whether the documented retail predictability persists in more recent market conditions. We show that this pronounced predictability disappears in the more recent 2017-2022 period.¹¹ Third, we provide a unifying explanation for the mixed conclusions in the existing literature: retail trading predictability is more consistent with a friction-based explanation than with superior information, as it arises from trading concentrated in small and illiquid stocks, where demand shocks are slow to be absorbed.¹² As liquidity improves in these segments of the market, the return predictability of retail trading dissipates.

Our findings also speak to the growing literature on the role of social media in shaping retail behavior across online platforms such as Seeking Alpha, Robinhood, Twitter, and WallStreetBets (e.g., Farrell et al., 2022; Eaton et al., 2021; Behrendt et al., 2018; Bradley et al., 2024). We complement this literature by showing that although social media can amplify short-term retail demand shocks, its ability to generate persistent return predictability diminishes as liquidity improves. We also show that the deterioration in predictability, particularly among small

¹⁰ The informational content of retail trades has also been shown to vary with holding horizon (Barber and Odean, 2008) and across broker types (Fong et al., 2014).

¹¹ We also find a consistent decline in predictability using data obtained with BJZZ's methodology (see Table IA-1, Panel A). Hence, the original predictability in BJZZ and the decline are not driven by issues with their methodology.

¹² Consistent with prior evidence, we find that retail investors tilt toward small and value stocks on average. Kumar and Lee (2006) document that retail investors disproportionately hold small and value stocks. In our data, these tilts contribute to the predictability observed in the early part of the sample.

stocks, is not driven by changes in retail investor sophistication but instead reflects structural improvements in liquidity.

We also study whether regulatory changes affecting market structure contributed to the decline in retail trading predictability by examining the impact of the TSPP. While prior literature shows that the TSPP altered trading activity and market quality, influencing trading costs and price formation (e.g., Comerton-Forde et al., 2019; Albuquerque et al., 2020; Chung and Chuwongnant, 2023), our findings complement this literature by showing that the TSPP led to a sharp contraction in retail trading, which weakened retail-driven price pressure and reduced return predictability.

Finally, our paper relates to broader literature on the role of liquidity in shaping equity market efficiency. Prior studies show that liquidity enhances pricing efficiency in futures-cash markets (Roll et al., 2007), reduces intraday return predictability arising from order flows (Chordia et al., 2008), and attenuates the economic and statistical significance of anomalies (Chordia et al., 2014). We provide new evidence from retail trading, consistent with the view that improvements in liquidity, particularly among small stocks, reduce the price impact of retail-driven demand shocks and thereby eliminate the return predictability associated with retail order flow.

2. Data

We use daily retail flow data (in US dollars) for US stocks provided by VandaTrack from January 3, 2014, to December 31, 2022. VandaTrack is a proprietary data platform developed by Vanda Research that provides daily data of retail buying and selling for individual US-listed stocks. The dataset is designed to meet the needs of professional investors, financial research firms, and more recently, academic researchers looking to systematically track retail trading activity.¹³

¹³ For example, see <https://www.businessinsider.com/dataset-for-hedge-funds-tracking-retail-traders-inside-vandatrack-2021-11>.

According to the provider, their algorithm improves upon the BJZZ approach through proprietary adjustments aimed at improving measurement accuracy.¹⁴ Although the specific refinements are not publicly disclosed, empirical evidence indicates that the VandaTrack measure is less noisy and contains incremental predictive information that is not subsumed by the BJZZ proxy. We provide a detailed comparison of the two datasets in the Internet Appendix. To mitigate biases arising from short coverage histories, we restrict the sample to stocks that are tracked by VandaTrack for at least three consecutive years, resulting in an average daily coverage of 2,724 stocks. Data on stock characteristics are obtained from the CRSP daily and monthly stock databases, while fundamental variables are from the COMPUSTAT quarterly and annual files. Our sample focuses on common stocks listed on the three main US exchanges. To mitigate microstructure distortions and extreme price effects, we exclude firms with a minimum share price below \$1 at the previous month-end.

Similar to the prior literature (e.g., Barber et al., 2024; BJZZ), we measure retail trading activity by computing retail flow imbalance for each stock i on each day t :¹⁵

$$mroibflow_{i,t} = \frac{Buy\ flow_{i,t} - Sell\ flow_{i,t}}{Buy\ flow_{i,t} + Sell\ flow_{i,t}}$$

Table 1, Panel A presents time-series cross-sectional averages of the mean, median, standard deviation, minimum, and maximum values computed from daily data over the 2014-2022 period. Average daily retail buy flow is \$1.151 million, while average daily retail sell flow is slightly lower at \$1.068 million. The average retail flow imbalance ($mroibflow$) across the entire sample period is -0.005, indicating a modest dominance of selling over buying. Panel B illustrates shifts in retail trading behavior across subperiods. During 2014-2016, the average $mroibflow$ was

¹⁴ Some academics raised concerns on the BJZZ methodology. For example, Barber et al. (2023) tests the accuracy of BJZZ's algorithm by placing 85,000 retail trades in six retail brokerage accounts and find that only 35% of orders are from retail investors.

¹⁵ The measure proposed by BJZZ actually uses number of shares instead of \$ amounts. When we divide the daily retail flow from VandaTrack by the daily closing price from CRSP, we obtain consistent results.

-0.019, reflecting notably stronger net retail selling. In the 2017-2019 period, the average imbalance turned positive (0.003), implying a transition toward net retail buying. This trend intensified during 2020-2022, then *mroibflow* increased to 0.013, indicating a substantial rise in net retail buying activity during the post-pandemic period.

To examine changes in retail trading behavior over time, we analyze retail activity across firms with different exposures to size, book-to-market ratio, and momentum characteristics in each sub-period. To capture the relative importance of retail trading compared to overall market activity, we compute normalized retail trading activity (NTA I) following Kumar and Lee (2006) (see Eq. (1)). Because institutional flows have grown substantially in recent years (e.g., Appel et al., 2016; Kojien et al., 2020), we also construct an alternative measure, NTA II, which scales retail trading by market capitalization to capture the concentration of retail trading independent of institutional volume trends. We report average values of both NTA I and NTA II across portfolios sorted by size, B/M, and momentum characteristics based on DGTW classifications. The sample is divided into two subperiods, 2014-2016 and 2017-2022.

$$NTA I_{i,t} = \frac{\text{Retail flow from retail investors in the sample}}{\text{Total flow in the market}} \times 10^6,$$

$$NTA II_{i,t} = \frac{\text{Retail flow from retail investors in the sample}}{\text{Market capitalization}} \times 10^6 \quad (1)$$

Panel B shows that average NTA II increases from 0.269 in 2014-2016 to 0.403 in 2017-2022, whereas NTA I declines from 0.039 to 0.032. This divergence implies that, despite the rise of retail flows, institutional trading has grown at a faster pace, reducing the relative importance of retail activity. Retail buy flows increase more than sell flows, generating a positive retail flow imbalance across most stock categories, except small-cap stocks. In 2014-2016, retail investors show a strong preference for small stocks, with NTA II equal to 0.282 compared to 0.216 for large stocks. This preference intensifies in 2017-2022, as NTA II for small stocks rises sharply to 0.540.

However, the relative importance of retail trading in small stocks declines more significantly than in other categories (NTA I falls from 0.055 vs. 0.044), indicating that institutional participation expands even more rapidly. Large stocks experience a more modest decline in relative retail importance, with NTA I decreasing from 0.039 to 0.033. Retail trading continues to tilt toward value stocks relative to growth stocks. During 2014-2016, NTA II is 0.384 for growth stocks versus 0.235 for value stocks, and this gap persists in 2017-2022, with values of 0.513 and 0.398, respectively. Moreover, retail investors exhibit a stronger tilt toward losing stocks relative to winning stocks. NTA II for losers versus winners is 0.373 versus 0.313 in 2014-2016 and increases to 0.643 versus 0.431 in 2017-2022. Consistent with this shift toward contrarian behavior, retail flow imbalance for losing stocks turns positive (0.008) in the 2017-2022 period, suggesting increased buying of losers, consistent with Luo et al. (2025).

[Table 1]

3. Predictability of retail trading for stock returns

This section documents the disappearance of return predictability associated with retail trading over the 2014 – 2022 period and investigates the mechanisms underlying this pattern. We begin by reassessing the predictive power of retail flow imbalance and show that the strong predictability observed in the early part of the sample diminishes and ultimately disappears in later years. We then examine the cross-sectional drivers of this decline, showing that predictability is concentrated in small and illiquid stocks and is largely explained by systematic factor exposures. Next, using portfolio and vector autoregression analyses, we show that increases in liquidity Granger-cause a decline in the returns of trading strategies that exploit this predictability. Finally, we explore the role of active investors, such as institutional investors and short sellers, in

facilitating the absorption of retail-driven demand imbalances and provide complementary evidence based on variation in liquidity around Russell index reconstitution.

3.1. Evolution of retail trading predictability

As in BJZZ, we estimate the predictive power of weekly retail flow imbalance for future stock returns using Fama-MacBeth regressions (1973). In Eq. (2), the dependent variable is the weekly return over the next k weeks ($k = 1, 2, \dots, n$). The independent variable is the weekly retail flow imbalance. To avoid the overlapping problem inherent in daily-frequency data and to mitigate concerns related to Monday and Friday effects (e.g., French, 1980; Keim and Stambaugh, 1984; Kiyamaz and Berument, 2003; Birru, 2018), we construct all weekly variables by cumulating daily data from Wednesday through the following Tuesday. Following BJZZ, we include the following control variables: current weekly returns and turnover, previous monthly returns and return volatility, and cumulative returns over the prior six months. To account for serial correlation in the time-series of coefficient estimates, we adjust standard errors using the Newey-West method (1987). Observations from January 2020 to April 2020 are excluded to mitigate the impact of market disruptions due to the COVID-19 shock.¹⁶

$$Ret_{i,w+k} = \beta_{0,w} + \beta_{1,w} mroibflow_{i,w} + \Gamma_w Controls_{i,w} + \varepsilon_{i,w+k}, k = 1, 2, \dots, n. \quad (2)$$

We find strong evidence of return predictability from retail flow imbalance during the 2014-2016 period, but this effect disappears in subsequent years. Table 2 shows that the coefficient on this variable (β_1) is positive and statistically significant during 2014-2016, indicating that net retail buying is followed by higher returns, whereas net retail selling predicts lower returns. The predictive effect remains significant for up to five weeks ahead. Although this horizon is somewhat

¹⁶ Ozik et al. (2021) find that retail investors provided liquidity during the COVID-19 shock, when market stressed and retail demand temporarily substituted for institutional liquidity provision. However, we do not observe similar behavior during normal market conditions. To assess the general impact of retail trading, we exclude the COVID-19 shock period from our analysis.

shorter than the eight-week window documented in BJZZ for 2010-2015, the overall conclusion remains consistent: retail trading positively predicts near-term returns. Differences in magnitude and duration likely reflect the shorter sample period, as the VandaTrack data begin in 2014.¹⁷ In contrast, during the 2017 to 2022 period, predictive power is no longer present, with coefficients close to zero and statistically insignificant. In untabulated results, we further test for differences in coefficients across the two periods using a pooled Fama-MacBeth framework over the full 2014 - 2022 sample. The results show statistically significant differences in the coefficients in retail flow imbalance for returns over the first five subsequent weeks between the two periods.

[Table 2]

To examine the evolution of retail predictability, we conduct a year-by-year analysis. Table 3 shows that during the 2014-2016 period, retail flow imbalance exhibits strong and persistent predictive power for future returns, with statistically significant effects extending up to six weeks ahead. In 2014, the predictability reverses in the seventh week, likely reflecting a correction of the initial price impact induced by retail demand pressure. By 2016, however, the horizon of predictability has already begun to contract, with significance persisting only through four weeks, indicating early signs of attenuation. Beginning in 2017, retail flow imbalance no longer displays statistically significant predictive power even at the one-week horizon and this absence of predictability continues throughout the remainder of the sample. To further investigate the timing of the decline in return predictability from 2016 to 2017, we estimate 20-week rolling averages of Fama-MacBeth coefficients from weekly cross-sectional regressions of next-week stock returns on retail flow imbalance over the 2015 – 2018 period. Figure 1 shows that predictability begins to

¹⁷ To ensure that the deterioration in predictability is not an artifact of the VandaTrack database, we also construct retail trading data using the methodology of BJZZ. As shown in Table IA-2, the results remain consistent: return predictability is strong during 2014-2016 but diminishes sharply thereafter.

diminish in the first week of October 2016, with the coefficient declining from about 0.08% to zero. The coefficient remains statistically insignificant from February 2017 onward, aside from occasional weeks. Given this clear structural breakpoint in predictive strength, we divide the sample into two subperiods: the 2014-2016 period, during which retail trading consistently predicts future returns, and the 2017-2022 period, during which this predictive relation disappears, to investigate the possible economic mechanisms underlying the observed decline.

[Table 3]

[Figure 1]

3.2. Sources of predictability

We next investigate whether the predictability of retail flows, and its evolution, originates from the buy side, the sell side, or both. We sort stocks into quartiles based on their weekly retail flow imbalance, where the bottom quartile represents stocks experiencing the strongest retail selling relative to buying, and the top quartile represents those with the strongest buying relative to selling. To explore asymmetric predictability across buying and selling dominance, we apply piecewise linear regressions (Sirri and Tufano, 1998) which allow heterogeneous sensitivities of future returns to retail trading across quartiles. Specifically, we introduce four dummy variables: $D_{1,2,3,4,w}$, each equal to one when a stock's weekly retail flow imbalance falls within the corresponding quartile. We then modify Eq. (2) by replacing the single *mroibflow* term with four interaction terms between *mroibflow* and these quartile indicators. The coefficients on these interaction terms capture the conditional predictive effects of retail flows on next week's returns within each quartile. Everything else remains the same as described in Eq. (2).

Table 4 shows that, during the 2014-2016 period, the persistent predictive power of retail trading over the next five weeks primarily arises from the top quartile of retail flow imbalance,

implying that stocks most aggressively bought and least sold by retail investors subsequently earn higher returns. The bottom quartile also exhibits a positive coefficient, but the effect is only marginally significant and limited to the first week, suggesting that stocks with the strongest retail selling pressure tend to exhibit only modest short-term lower subsequent returns. In contrast, the 2017-2022 period reveals no evidence of predictability in any quartile. Overall, the strong return predictability in the 2014-2016 period, which was concentrated in the most heavily bought and least sold stocks, disappears in the later period.

[Table 4]

Next, we examine whether the predictive power of retail trading persists after controlling for exposures to size, book-to-market, and momentum characteristics. To control for return variation unrelated to these characteristics, we replace raw returns with DGTW characteristic-adjusted returns (Daniel, Grinblatt, Titman, and Wermers, 1997) in Eq. (2). Table 5 shows that, during the 2014-2016 period, both the magnitude and statistical significance of the coefficients associated with the top quartile of retail flow imbalance are substantially reduced. These results suggest that the earlier predictability of retail trading is largely driven by systematic tilts toward size, book-to-market, and momentum characteristics. Once these factor exposures are accounted for, the remaining predictive effect of retail trading reflects a limited informational component related to future returns.

[Table 5]

To better understand how standard factor exposures contribute to the predictive power of retail trading, we begin by examining the role of firm size, given the disproportionately aggressive retail activity in small-cap stocks. We classify stocks into three size categories based on quarterly DGTW size portfolio rankings. Specifically, small stocks are those assigned to size quintile

portfolios “1” or “2”. Medium stocks fall into quintile “3”. Large stocks are those in quintiles “4” or “5”. Because the results in Table 4 indicate that return predictability is concentrated in the top quartile of retail flow imbalance, we construct three interaction terms between the top-quartile retail flow imbalance and the size indicators: Top 25% *mroibflow**Small, Top 25% *mroibflow**Medium, and Top 25% *mroibflow**Large, which allow us to quantify whether the predictive effect of strong retail buying varies across size groups. We retain the original interactions between *mroibflow* and its quartile indicators (bottom 25%, bottom 25% - bottom 50%, and top 50% - top 25%) within the Fama-MacBeth (1973) framework to ensure comparability with earlier specifications. In Eq. (3), the dependent variable is the weekly abnormal return controlled for book-to-market and momentum characteristics, computed as the cumulative daily return minus the cumulative daily return of the stock’s corresponding DGTW 5x5 B/M - Momentum portfolio. Control variables and Newey-West standard errors remain identical to those in Eq. (2).

$$\begin{aligned}
ABRet_{i,w+k} = & \beta_{0,w} + \beta_{1,w}mroibflow * D1_{i,w,top\ 25\%} * Small_{i,q-1} \\
& + \beta_{2,w}mroibflow * D1_{i,w,top\ 25\%} * Medium_{i,q-1} \\
& + \beta_{3,w}mroibflow * D1_{i,w,top\ 25\%} * Large_{i,q-1} + \Gamma_w Controls_{i,w} \\
& + \varepsilon_{i,w+k}, \tag{3}
\end{aligned}$$

Table 6, Panel A shows that the predictive power of the top quartile of retail flow imbalance is concentrated exclusively in small stocks. The coefficient on the Top 25% *mroibflow**Small interaction is positive and significant (0.042), indicating that small stocks experiencing the strongest net retail buying pressure earn higher returns in the subsequent week. This predictive effect persists for up to five weeks, suggesting a sustained influence on small stock performance

during the 2014-2016 period.¹⁸ In contrast, during the 2017-2022 period, retail flow imbalance does not display predictive power even within small stocks, indicating that the decline in retail predictability is related to small stocks.

We next investigate potential explanations for the decline in predictability among small stocks. As shown in Table 1, Panel B, both retail and institutional investors substantially increased their trading activity in small stocks during the 2017 to 2022 period, potentially enhancing the liquidity of these stocks. With higher liquidity, retail trading is less likely to exert meaningful or persistent price impact. The weaker price response also reduces the visibility of these stocks to other retail investors, who may engage in attention-grabbed trading triggered by imbalanced retail buying or extreme short-term returns (e.g., Lou, 2014; Gervais et al., 2001). Consequently, fewer retail investors are prompted to buy and hold these stocks following initial retail order imbalances, limiting the extent to which retail-driven demand pushes price upward in subsequent weeks. We measure stock-level illiquidity using the Amihud (2002) illiquidity ratio, which reflects price impact and is computed quarterly as the average of absolute daily returns divided by dollar trading volume, multiplied by 10^6 and winsorized at the 1st and 99th percentiles.¹⁹ Table 6, Panel B, reports descriptive statistics for illiquidity across the two subperiods. Small stocks are consistently more illiquid than the overall sample (80.115 vs. 45.756 during 2014-2016 and 34.064 vs. 19.867 during 2017-2022) and illiquidity among small stocks declines by more than half across the two periods (from 80.115 to 34.064). This substantial improvement in liquidity motivates our hypothesis that increased liquidity contributes to the decline in retail trading predictability among small stocks. To test this hypothesis, we sort stocks each quarter into high- and low-liquidity

¹⁸ In untabulated results, we also find that the predictive effect associated with the bottom quartile is concentrated in small stocks at the one-week horizon.

¹⁹ We use quarterly illiquidity to keep consistence with the size sorting in DGTW characteristic-quarterly-adjusted portfolios. We also check annual and month liquidity measures, and the results are consistent.

groups based on illiquidity and construct liquidity indicators that are interacted with the top quartile of retail flow imbalance across size categories (Small, Medium, or Large), while retaining the original interactions between *mroibflow* and its quartile indicators.

Table 6, Panel C, shows that the predictive power of top-quartile retail flow imbalance is concentrated exclusively in small stocks with low liquidity, while no statistically significant predictability is observed for small stocks with high liquidity. This finding supports our hypothesis that liquidity conditions play an important role in explaining the return predictability of retail trading during the 2014-2016 period. In unreported results, a similar analysis for the bottom quartile of *mroibflow* produces the same conclusion: predictive effect stems only from small stocks with low liquidity. Overall, the deterioration of retail predictability in the later period appears at least partly attributable to the loss of predictability among small and illiquid stocks that experienced significant liquidity improvements, which reduce the price impacts of retail-induced demand imbalances and weakens the informational content embedded in retail trading activity.

[Table 6]

We apply the same framework used for size characteristics to assess whether book-to-market explains the deterioration in retail predictability. Stocks are classified into growth (quintile “1” or “2”), neutral (quintile “3”), and value (quintile “4” or “5”) groups based on quarterly DGTW B/M rankings and we interact these indicators with the top quartile of retail flow imbalance. The dependent variable is weekly abnormal return, calculated as the cumulative daily return in excess of the cumulative daily return of the corresponding DGTW 5x5 Size-Momentum benchmark portfolio. Table IA-3 shows that, during 2014-2016, retail flow imbalance exhibits positive and significant predictive power for value stocks, persisting up to five weeks. This pattern continues

in 2017-2022, indicating that B/M characteristics contribute to retail trading predictability but do not explain its overall decline.

With respect to momentum, Table IA-4 shows that, beyond the one-week horizon, top-quartile retail flow imbalance does not significantly predict returns across momentum groups, and the one-week relation does not systematically load on momentum exposures. The limited one-week effect is therefore more consistent with transitory demand shocks than with information related to momentum continuation or reversal. Motivated by earlier results that predictability is concentrated in small, illiquid stocks and recognizing that DGTW-adjusted returns control only at the characteristic-portfolio level, we further conduct subsample analyses jointly by size and liquidity. Table IA-5 shows that predictability across losing, neutral, and winning stocks is confined to small stocks with low liquidity. Once size and liquidity effects are accounted for, retail flow imbalance no longer predicts returns across momentum categories. In the 2017-2022 period, no momentum-based predictability is detected. Alternative momentum definitions based on one- and three-month returns yield similar conclusions. Overall, retail investors do not exhibit systematic predictive ability with respect to either past losers or winners, despite a growing tendency toward contrarian trading in the later period.²⁰

So far, our findings indicate that the return predictability of retail trading is substantially reduced once we control for size, book-to-market, and momentum characteristics through DGTW-adjusted returns. Furthermore, we show that the observed decline in predictability can be partly attributed to the weakening influence of retail trading on small stocks, whose liquidity has

²⁰ Consistent with this view, Luo et al. (2025) indicate that contrarian retail trading does not reflect superior information or skill but instead is associated with behavioral biases, including conservatism (Edwards, 1968), whereby investors are slow to update their price expectations and perceive prices as having overreacted, and the law of small number (Tversky and Kahneman, 1971), whereby investors expect reversals following short sequences of good or bad news.

improved markedly over time. To clearly investigate the roles of size and liquidity, we conduct a separate analysis focusing on small stocks with low liquidity relative to all other stocks during the 2014-2016 period. In Eq. (4), we construct two dummy variables, *SL* and *Other*. *SL* equals one for small stocks with low liquidity. *Other* equals one for the remaining stocks. We interact the weekly retail flow imbalance with each stock-type indicator. Because the predictability for value stocks remains stable throughout the 2014-2022 period, we control for book-to-market exposures, and the dependent variable is the weekly return net of book-to-market characteristics. We also interact quartiles of retail flow imbalance with the *SL* and *Other* indicators.

$$\begin{aligned}
 ABret_{i,w+k} = & \beta_{0,w} + \beta_{1,w}mroibflow_{i,w} * SL + \beta_{2,w}mroibflow_{i,w} * Other + \Gamma_w controls_{i,w} \\
 & + \varepsilon_{i,w+k},
 \end{aligned} \tag{4}$$

Table 7 shows that, during 2014-2016, the predictive power of retail flow imbalance over the subsequent five weeks is concentrated entirely among small, low-liquidity stocks. The quartile-based decomposition further indicates that this persistent predictability originates primarily from the top quartile of *mroibflow*, with the bottom quartile yielding only a short-lived positive effect at the one-week horizon among these illiquid small stocks. Overall, these findings indicate that, once exposures to common equity factors and liquidity are accounted for, retail trading exhibits little meaningful predictive power for future abnormal returns even during 2014 – 2016, consistent with the absence of predictability observed in the 2017 – 2022 period. The results remain robust when the predictability is re-estimated using subsample analyses rather than interaction specifications. Table IA-2, Panel B reports consistent results using a retail trading measure constructed following the BJZZ methodology. Table IA-6 shows that replacing the liquidity proxy with the percentage of the bid-ask spread yields consistent findings, further reinforcing the robustness of our conclusions. Thus, the evidence suggests that the decline in retail trading

predictability does not appear to reflect a deterioration in retail investors' trading skill or information advantage. Instead, it points to structural changes in market conditions. As liquidity improved, retail trades became less influential in price formation, reducing the extent to which retail flow imbalance can forecast subsequent returns. Additional evidence (see Section 4.2 and in particular Table 13, Panel B and C) indicates that the observed predictability reflects persistent retail demand shocks. In particular, we find that the persistent component of retail flows exhibits predictive power only among small stocks with low liquidity, consistent with slow absorption of order imbalances in these segments of the market.

[Table 7]

3.3. Portfolio analysis

We further assess retail trading predictability during the 2014-2016 period using a portfolio analysis to examine whether the documented predictability translates into economically meaningful portfolio performance. Specifically, each week, we sort stocks into deciles based on retail flow imbalance and construct equal-weighted portfolios. Portfolio P10 comprises stocks in the highest decile of *mroibflow* (i.e., strong net retail buying), while portfolio P1 comprises stocks in the lowest decile (i.e., strong net retail selling). Small and illiquid stocks are identified using the same criteria in the preceding analyses. We report both raw returns and returns adjusted for book-to-market exposures. Table 8 shows that the P10 portfolio of small and illiquid stocks earns positive returns over the subsequent four weeks. Furthermore, a zero-investment strategy that takes a long position in P10 and a short position in P1 yields significantly positive returns for small and illiquid stocks over horizons of up to five weeks, but not for other stocks. These results support our main finding that retail predictability during the 2014-2016 period is concentrated among small stocks with low liquidity. The return to this strategy peaks in the first week and gradually attenuates

over the following four weeks. We also consider a second zero-investment strategy that goes long the P10-P1 spread within the small and illiquid stock group and shorts the corresponding spread within remaining stocks. This strategy generates positive returns that are statistically significant in the first and third weeks. The similarity of results based on raw and book-to-market-adjusted returns indicates that the predictive effect among small and illiquid stocks is not driven by value-related exposures and confirms that book-to-market characteristics do not explain the decline in overall predictability.

[Table 8]

3.4. Vector autoregression analysis

To provide direct evidence that the decline in illiquidity among small stocks contributes to the weakening predictive power of retail trading, we estimate a vector autoregressive (VAR) model that jointly examines the dynamics of illiquidity and the returns of the long-short portfolio that exploits the predictability of retail trading activity. Specifically, inspired by Chordia et al. (2014), we estimate the following system, where y_t is a vector containing the level of illiquidity and the weekly long-short portfolio return constructed in the previous portfolio analysis (P10-P1):

$$y_t = c + B_1 y_{t-1} + B_2 y_{t-2} + \varepsilon_t \quad (5)$$

The VAR system is estimated with two lags, selected according to the Schwarz Bayesian Information Criterion. Prior to estimation, we assess the time-series properties of each variable using augmented Dickey-Fuller tests and find no evidence of nonstationarity. We conduct the analysis separately for the subsample of small stocks and the full sample of all stocks to examine whether illiquidity is a relevant driver of retail predictability only among small stocks or also at the aggregate stock level. Table 9 reports the cumulative coefficients on the two lags of illiquidity, along with p-values from F-tests for their joint significance. We also present p-values from

Granger-causality Wald tests, which provide a formal assessment of whether lags of illiquidity explain returns on the retail-based long-short portfolio. Across both the small-stock subsample and the full sample, the evidence consistently indicates that lagged illiquidity is positively and significantly associated with portfolio returns. This evidence is consistent with our hypothesis that improvements in stock liquidity (i.e., reductions in illiquidity), particularly among small stocks, weaken the predictive power of retail order flow for future returns. Stability diagnostics confirm that all eigenvalues lie inside the unit circle, indicating that the VAR satisfies the stability condition. Moreover, we find no evidence of reverse causality from portfolio returns to illiquidity. These findings indicate that the direction of Granger causality operates as hypothesized, from stock illiquidity to retail-based returns. Finally, we assess whether this relationship remains robust after controlling for macroeconomic conditions. Table IA-12, Panel A confirms that the Granger-causal link between lagged illiquidity and the retail-based portfolio returns persists, indicating that the relation is not materially driven by macroeconomic fluctuations.

[Table 9]

3.5. The role of active investors

Greater participation by active institutional investors and short sellers can enhance market depth and resiliency, allowing retail-induced demand imbalances to be absorbed more rapidly and reducing their price impact and persistence. If low liquidity in small stocks is an important driver of retail trading predictability, the effect observed during 2014 – 2016 should be stronger or more persistent among small stocks with low or declining participation by transient institutional investors and short sellers, where demand imbalances may be offset more slowly. Transient institutions, as short-term investors, are typically more responsive to short-term return patterns and liquidity conditions and have been shown to be more active in exploiting inefficiencies (see Ke

and Ramalingegowda 2005 and Calluzzo et al. 2019). Similarly, short sellers may facilitate downward price adjustments when valuations become inflated. Accordingly, limited institutional and short-seller participation may allow retail-driven price pressure to persist longer, sustaining return predictability. We measure institutional trading using the Thomson Reuters 13F database. Institutional investors with investment discretion over at least \$100 million in Section 13(F) securities are required to report their holdings to the SEC on Form 13F within 45 days of each quarter-end. We then use Bushee's classifications²¹ on reported institutions to further identify transient institutional investors.

Each quarter, we sort all stocks into quintiles based on (i) transient institutional ownership and (ii) changes in the ownership. We designate stocks in the bottom two quintiles of ownership and the bottom two quintiles of ownership change as those with low or decreasing institutional presence. We then construct two indicator variables: SLT which equals one for small stocks with low or declining transient ownership, and Other, which equals one for all remaining stocks. Weekly retail flow imbalance is then interacted with SLT and Other to test whether retail predictability varies with institutional trading activity. The dependent variable is the weekly return controlled for the book-to-market characteristics. We apply a similar logic to short-selling activity. Short-interest data, obtained from Bloomberg and updated bi-weekly, provides the number of shares short for each stock. We compute the short-interest percentage as the number of shares sold for short divided by total shares outstanding. We sort stocks into quintiles based on short-interest percentage and change in the percentage. Stocks in the lowest two quintiles of short-interest percentage or its changes are classified as having low or decreasing short-selling pressure. Based

²¹ For more details, see <https://accounting-faculty.wharton.upenn.edu/bushee/>

on this classification, we construct two analogous indicator variables: SLS, which equals one for small stock with low or declining short interest, and Other.

Table 10 shows that, beyond the one-week horizon, the predictability of retail flow imbalance is concentrated entirely among small stocks with low or declining ownership by transient institutional investors. Although retail trading also predicts next-week returns for the remaining stocks, the magnitude is roughly half that observed in the low-transient-ownership group (0.034 vs. 0.061). Conditioning on short-selling activity yields a similar pattern. Return predictability over the subsequent five weeks is primarily driven by small stocks with low or decreased short-interest percentage, and the one-week effect is both economically stronger and statistically more significant than their counterparts (0.065 vs. 0.021).²² We further estimate a VAR model to examine the joint dynamics between short-interest percentage and the long-short weekly portfolio returns derived from retail trading. Table IA-7 shows that lagged short-interest percentage negatively Granger-causes the hedged portfolio returns, consistent with the idea that greater short-selling participation dampens the predictive effect of retail order flow.^{23,24} Overall, the evidence is consistent with the view that greater trading capacity, from higher participation by transient institutional investors and short sellers, reduces the persistence of retail-induced price pressure and significantly attenuates the predictive power of retail trading. In stocks where such participation is limited, retail-induced demand imbalance is less likely to be absorbed quickly,

²² One alternative explanation is that retail investors may observe decreases in short-interest and interpret them as signals of future price increases, promoting them to buy. Under this view, the predictability of retail trading would simply reflect retail investors' ability to anticipate short interest ratio. However, our evidence does not support this interpretation. When we sort stocks by short-interest percentage within large stocks, where liquidity is high and informed trading by institutions is more prevalent, retail flow imbalance does not exhibit predictive power.

²³ We also find a positive causal effect in the reverse direction, reflecting that short sellers tend to increase their positions following periods in which retail-driven price pressure elevated returns. This pattern is consistent with the notion that arbitrageurs respond to noise-trader demand and subsequently correct mispricing (e.g., Collin-Dufresne and Fos, 2015; 2016; Cookerson et al., 2022).

²⁴ We do not estimate a VAR model for transient institutional ownership because the quarterly frequency of this variable provides insufficient time-series variation for a weekly VAR framework.

allowing its price impact to persist and generate stronger return predictability.

[Table 10]

In addition to institutional participation, structural changes in retail trading activity may also have contributed to improvements in market liquidity. The rapid expansion of mobile brokerage platforms, such as Robinhood, and the sharp decline in trading commissions after 2016 substantially increased retail trading activity and market participation.^{25, 26} Furthermore, in September 2017, TD Ameritrade completed its acquisition of Scottrade, absorbing more than three million retail accounts and approximately \$24 billion in client assets.²⁷ This consolidation migrates a large population of self-directed retail investors to a more technologically advanced trading platform with faster execution and more efficient order routing. Retail order flows could be absorbed more quickly by market makers and other liquidity providers, improving market liquidity and accelerating price adjustment. All these developments likely increased overall market depth and facilitated faster absorption of order flow imbalances. While we do not directly quantify their impact, they are consistent with the broader improvement in liquidity documented in the data.

3.6. Russell Index Reconstitution and Variation in Liquidity and Predictability

This subsection examines changes in retail trading predictability around Russell index reconstitution, which provides a widely used source of variation in market conditions. While index reconstitution has often been interpreted as generating plausibly exogenous variation, Wei and

²⁵ Robinhood's user base doubled from roughly one million funded accounts in 2016 to about two million in 2017, making the earliest and sharpest expansions in mobile-app brokerage growth. User growth continued to accelerate in subsequent years and intensified further during the COVID-19 period. For more details, see <https://investinginthetweb.com/brokers/robinhood-statistics>

²⁶ In March 2017, major brokerages responded to fintech competition by reducing online equity-trading commissions. Fidelity Investments cut its commission from \$7.95 to \$4.95, followed by similar cuts at Charles Schwab, TD Ameritrade, and E-Trade. For more details, see <https://www.wsj.com/articles/fidelity-drops-online-trading-commissions-by-38-to-4-95-each-1488258061>.

²⁷ For more details, see <https://www.bloomberg.com/news/articles/2016-10-24/td-ameritrade-toronto-dominion-buy-scottrade-for-4-billion>.

Young (2024) highlight potential selection concerns around index thresholds.²⁸ Accordingly, we interpret the evidence in this subsection as suggestive rather than providing definitive causal estimates. Importantly, our analysis does not rely on discontinuities in institutional ownership at index cutoffs. Instead, we focus on the associated changes in market liquidity, which we document directly in the data. Index reconstitution is accompanied by changes in trading activity and market depth, which can enhance the market’s capacity to absorb retail-driven demand imbalances. We therefore examine whether retail trading predictability weakens following index inclusion and strengthens following index exclusion.

Russell Inc. reconstitutes its indexes on the last Friday of June each year based on end-of-May stock capitalization rankings, and index composition remains constant until the following year. To mitigate the selection bias documented in Wei and Young (2024), we exploit within-stock variation in Russell 3000 membership by comparing retail predictability before and after a stock’s entry or exit. For index entry, we examine stocks within a cohort year that experience inclusion, while for index exit, we focus on stocks that experience exclusion.²⁹ Index inclusion is associated with increases in passive institutional demand, which prior studies show is associated with higher trading activity, greater market depth, and higher liquidity (e.g., Saglam et al., 2021; Agarwal et al., 2021).³⁰ We begin by examining the relation between Russell 3000 reconstitution and stock illiquidity. Table 11, Panel A shows that index entry is associated with a significant decline in

²⁸ Wei and Young (2024) demonstrate that the timing of Russell index reconstitution may be endogenous, as index entry is related to positive return shocks and momentum. Using a regression discontinuity design around the Russell 1000/2000 cutoff, they show that comparisons between entering and staying stocks are subject to selection bias, leading to an overestimation of the change in institutional ownership associated with index inclusion.

²⁹ We do not rely on the Russell 1000/2000 cutoff (e.g., Appel et al., 2015; Ben-David et al., 2018) because firms around that threshold are relatively large and already highly liquid. We find no evidence of retail trading predictability among stocks near this cutoff.

³⁰ Wei and Young (2024) find no significant change in institutional ownership around the Russell 1000/2000 cutoff. One possible explanation is that both indexes are widely followed and attract similar institutional demand. In contrast, our focus on the Russell 3000 boundary captures transitions into the Russell 000 from outside the index, which are more likely to generate meaningful changes in institutional trading and liquidity.

weekly illiquidity, whereas index exit leads to a corresponding increase. These results indicate that Russell reconstitution is accompanied by economically meaningful changes in liquidity.

We next assess retail trading predictability conditional on Russell 3000 reconstitution. In Eq. (6), the dependent variable is the weekly return net of book-to-market characteristics. *Entry* (or *Exit*) equals one for observations after June in the cohort year and zero otherwise. Under our hypothesis, liquidity improvements following index inclusion should attenuate the price impact of retail order flow and its predictability, while reduced liquidity following exclusions may restore it. To further mitigate selection concerns, all specifications include stock and year-week fixed effects to absorb time-invariant firm heterogeneity and common shocks. Standard errors are double-clustered at the stock and year-week levels to account for both cross-sectional and temporal dependence.

$$ABret_{i,w+1} = \beta_{0,w} + \beta_{1,w}mroibflow_{i,w} * Entry_{i,y} \text{ (or } Exit_{i,y}) + \beta_{2,w}mroibflow_{i,w} + \Gamma_w controls_{i,w} + \gamma_i + \delta_w + \varepsilon_{i,w+1}, \quad (6)$$

We find that retail trading predictability declines following index inclusion and increases following index exclusion (see Table 11, Panel B). This symmetric pattern is consistent with liquidity changes around index reconstitution affecting the absorption of retail-induced demand imbalances and, in turn, the return predictability. These findings provide additional evidence consistent with the view that improvements in liquidity play an important role in the decline of retail trading predictability. Our within-stock identification strategy, combined with fixed effects, help mitigate the selection concerns raised by Wei and Young (2024), which primarily affect cross-sectional comparisons. Although they argue that stocks entering the index exhibit higher volatility, positive price momentum, and increased institutional demand prior to reconstitution, we continue

to observe retail predictability before entry. Additionally, excluding the three months prior to reconstitution to mitigate potential pre-event dynamics yields consistent results.

[Table 11]

Taken together, the results in this section provide consistent evidence that the predictability of retail trading is concentrated in small, illiquid stocks and declines as liquidity improves, supporting the interpretation that retail-driven demand shocks generate temporary price pressure that is increasingly absorbed in more liquid market environments. While our analysis does not deliver a single clean causal estimate, the consistent evidence across cross-sectional, time-series, and institutional settings supports a liquidity-based interpretation of the results.

4. Other potential explanations for the decline in predictability.

This section examines additional mechanisms that may contribute to the decline in retail trading predictability. While the evidence in Section 3 highlights the role of market liquidity in reducing the impact of retail-driven demand shocks—and hence return predictability—other factors may also influence the strength of these demand imbalances and, more generally, contribute to the decline. We begin by analyzing the impact of the Tick Size Pilot Program (TSPP), a regulatory intervention that affects retail participation in small-cap stocks. Second, we examine whether the rise of social media contributes to the weakening of predictability by decomposing retail trading into its underlying components. Third, we investigate whether the decline reflects changes in the determinants of retail trading itself, including the role of abnormal retail flows. Finally, we assess the impact of macroeconomic conditions and other commonly used risk factors.

4.1. The Tick Size Pilot Program

We first examine the role of the TSPP, a regulatory intervention, which increased the minimum tick size for a subset of small-cap stocks. While the evidence in Section 3 highlights the

role of liquidity in reducing the impact of retail-driven demand shocks, the TSPP provides a complementary channel through which predictability may decline by affecting retail participation. By increasing trading costs and reducing execution flexibility, the program is associated with a reduction in retail participation, which in turn weakens demand-driven price pressure.

The U.S. Securities and Exchange Commission (SEC) implemented the TSPP on October 3, 2016, which temporarily increased the minimum tick size from one cent to five cents for a set of stocks with capitalization under \$3 billion.³¹ The program included 2,400 small-cap stocks, of which 1,200 were randomly assigned by the SEC to three treatment groups (400 stocks in each)³² and the remaining 1,200 to a control group. By widening the tick size, the TSPP altered the trading environment faced by retail investors. Anshuman and Kalay (1998)'s model predicts that a large tick size imposes large transaction costs on traders.³³ Consequently, retail investors may reduce trading activity in affected stocks or redirect their activity toward alternative stocks, particularly when the widened tick exceeds the existing bid-ask spread, which further discourages marginal retail participation. Therefore, we examine retail buy and sell volumes during the TSPP and over the six-month windows before and after the program across treated stocks, control stocks, and the remaining stocks.

Figure 2 shows that retail trading volumes in the treated group decline sharply during the TSPP relative to the control group, which exhibits a comparatively stable upward trend despite short-term fluctuations. At the same time, retail trading in other stocks increases shortly after the

³¹ For more details, see <https://www.finra.org/rules-guidance/key-topics/tick-size-pilot-program>

³² Stocks in groups 1 through 3 are all subject to an increase in the minimum quote increment from one cent to five cents. In addition, group 2 and 3 stocks must trade in five-cent increments. Group 3 stocks are further subject to a “trade-at” prohibition. Given that we observe a consistent decline in retail predictability across all three treated groups, we aggregate them into a single treated sample for the main analysis.

³³ When a retail investor's valuation falls between the prevailing best quotes and the next tick increment, substantial displayed depth on traditional make-take venue lowers the likelihood of execution (Comerton-Forde et al., 2019). To increase execution probability, the investor must offer at least one tick of price improvement, but such improvement may eliminate the expected profit implied by the investor's valuation.

TSPP's implementation. These patterns indicate that the widened tick size materially constrained retail participation in treated stocks and induced a reallocation of retail order flow toward control and the remaining stocks. This evidence is consistent with Chung and Chuwonganant (2023), who document a migration of market participants from pilot stocks to control stocks during the TSPP. Retail-induced demand shock constitutes the primary channel through which retail trading generates short-horizon return predictability (see below in Section 4.2). By dampening retail order flow in treated stocks, the TSPP plausibly reduced the magnitude of retail-driven demand imbalances and therefore attenuated retail predictability during the program period.

[Figure 2]

We then examine the predictability of retail trading across treated, control, and remaining stock groups in the pre-, during-, and post-TSPP periods. The pre-TSPP period spans January 1, 2014 to October 2, 2016, and the post-TSPP period spans September 29, 2019 to December 31, 2022. Table 12 shows that retail trading positively predicts future weekly returns for treated tocks prior to the TSPP (0.043),³⁴ but this relation disappears during the program period (-0.002). Table IA-8 further indicates that the decline is driven primarily by a reduction in the persistent component (from 0.248 to 0.001), consistent with a weakening of retail-induced demand shocks. In contrast, the control group exhibits no significant change in predictability between the pre- and during-TSPP periods (0.025 vs. 0.030). The slightly larger coefficient during the program likely reflects the observed increase in retail flows to control stocks. For the remaining stocks, which are predominantly mid- and large-cap stocks, retail trading does not generate persistent predictability in any period, consistent with our broader finding that retail return predictability is concentrated

³⁴ We only present the prediction results for the next three weeks due to space. The prediction of the treated and control stocks in the pre-TSPP program lasts up to five weeks.

among small-cap stocks. Overall, the sharp reduction in retail trading within treated stocks substantially attenuated retail-driven demand shock and, consequently, reduced return predictability during the TSPP. This mechanism is consistent with the pronounced decline in aggregate predictability from early October 2016 through 2017 shown in Figure 1. At the same time, the reallocation of retail flow from treated small stocks to larger stocks with greater market depth weakens price pressure effects and further diminishes aggregate predictability.³⁵ We observe no significant predictability in the post-TSPP periods, a pattern consistent with improved liquidity as shown in Table 3.

Importantly, this channel operates through changes in retail participation rather than through improvements in market liquidity. Consistent with prior studies (e.g., Comerton-Forde et al., 2019; Albuquerque et al., 2020), we find no evidence that the TSPP is associated with a systematic improvement in liquidity among treated stocks relative to controls. Indeed, in Figure 1 (c) we compare illiquidity levels between treated and control stocks and show that although illiquidity exhibits a downward trend over time, there is no statistically significant difference in monthly average liquidity between treated and control stocks during the program. This distinction helps isolate the role of demand-side forces from the liquidity channel emphasized in Section 3. While gradual enhancements in stock liquidity help explain the longer-term decline in retail predictability, the TSPP-induced reduction in retail participation among treated small-cap stocks appears to accelerate the short-run decline in predictability.³⁶ Taken together, these findings indicate that regulatory interventions that reduce retail participation can weaken retail-driven demand shocks and contribute to the decline in return predictability. While this mechanism

³⁵ Due to the data limitations, we can not provide exact evidence about the reallocation.

³⁶ One may argue that larger tick size may lead to larger analyst coverage, more information production, and increase in price efficiency. However, Albuquerque et al., (2020) find that the treated stocks experience higher pricing error and higher price delay, suggesting a decrease in price efficiency.

operates alongside the liquidity channel documented earlier, its effects are more localized and do not fully account for the broader disappearance of predictability over time.

[Table 12]

4.2. Social media and the decomposition of predictability of retail trading

We also explore whether social media activity influences the predictability of retail trading. Since 2015, Bloomberg has tracked the daily frequency of stock mentions on Twitter (tweets publication count) and the corresponding average daily sentiment of these tweets.³⁷ Because Twitter discussions disproportionately concentrate on large-cap stocks, we first sort firms into deciles by market capitalization and compute each stock's daily tweet count percentile within its respective size group. We then construct weekly measures by averaging the daily tweet percentiles and sentiment scores. Table 13, Panel A reports summary statistics for weekly tweet volume and sentiment. Average tweet volume per stock was slightly higher in the 2015-2016 period than in the 2017-2022 period (64.744 vs. 56.828), although the upper tail of the distribution expanded substantially in the later period (maximum of 83,405 vs. 45,562). Average sentiment score declines from 0.041 in 2015-2016 to 0.020 in 2017-2022, and the proportion of stock exhibiting negative sentiment increased from 29.446% to 36.908%. The rise in negative sentiment may be particularly salient for retail investors who employ contrarian strategies. Elevated pessimistic tone around stocks could draw retail attention toward recent losing stocks, helping explain the stronger positive retail flow imbalance toward losing stocks observed in Table 1, Panel B for the 2017-2022 period.

To examine whether social media activity influences the predictability of retail trading, we decompose retail flow imbalance following the two-step methodology of BJZZ. As specified in

³⁷ Bloomberg constructs tweet sentiment by collecting firm-related tweets and classifying each tweet as positive, negative, or neutral using finance-specific natural language processing algorithms. Firm level sentiment measures are than obtained by aggregating and normalizing tweet-level classifications within each day. These measures are also employed in previous literature, such as Gu and Kurov (2020) and Krystyniak et al. (2025).

Eq. (7) and (8), in the first step, we decompose weekly retail flow imbalance into components capturing flow persistence, contrarian behavior (i.e., liquidity provision), tweet volume, sentiment, and residual. As emphasized by BJZZ, this decomposition requires the empirical assumption that discussion intensity and sentiment affect retail trading. A growing body of literature (e.g., Farrell et al., 2022; Eaton et al., 2021; Behrendt et al., 2018) using Twitter and other platforms' data provides evidence consistent with this assumption, showing that retail investors respond to online attention, tone, and information diffusion. In the second step, we re-estimate the predictive regressions by replacing retail flow imbalance with the five components (each regressor interacted with the estimated coefficients plus the residuals and intercept). This approach allows us to isolate which specific channels drive the overall predictability attributed to retail order flow and to assess the incremental role of social media in shaping the direction and magnitude of these effects. To capture variation in Twitter discussion intensity, we define two dummy variables based on the previous week's tweet volume percentile: *High* which equals one when the stock's tweet count percentile exceeds 50%, and *Low* otherwise. Similarly, to capture sentiment polarity, we introduce two dummy variables: *Positive*, which equals one when the average sentiment score in the previous week is above zero, and *Negative* otherwise. Then we interact these four dummy variables with tweet volume and sentiment related components of retail flow imbalance to examine how the influence of social media on retail trading varies depending on both the intensity of online discussion and sentiment.

$$mroi\widehat{b}flow_{i,w} = \gamma_0 + \gamma_1 mroi\widehat{b}flow_{i,w-1} + \Gamma_2 ret_{i,w-1} + \gamma_3 tweet_{i,w} + \gamma_4 sent_{i,w} + \varepsilon_{i,w} \quad (7)$$

$$ABret_{i,w+1} = \beta_0 + \beta_1 mroi\widehat{b}flow_{i,w}^{persistence} + \beta_2 mroi\widehat{b}flow_{i,w}^{contrarian} + \beta_3 mroi\widehat{b}flow_{i,w}^{other} + \beta_{4-7} mroi\widehat{b}flow_{i,w}^{sent+twit} \cdot D_{sent=+or-,i,w} \cdot D_{tweet=high\ or\ low,i,w} + \theta_{i,w+1}, \quad (8)$$

where

$$m\widehat{roibflow}_{i,w}^{persistence} = \gamma_1 \cdot mroibflow_{i,w-1},$$

$$m\widehat{roibflow}_{i,w}^{contrarian} = \Gamma_2 \cdot ret_{i,w-1},$$

$$m\widehat{roibflow}_{i,w}^{other} = \gamma_0 + \varepsilon_{i,w},$$

$$m\widehat{roibflow}_{i,w}^{sent+twit} = \gamma_3 \cdot tweet_{i,w} + \gamma_4 \cdot sent_{i,w}$$

The odd columns of Table 13, Panel B, present the decomposition of retail prediction without social media variables, whereas even columns incorporate social media components. Column (1) shows that, during the 2015-2016 period, retail trading predictability is primarily driven by the persistent component of retail flows and the residual “other” component, consistent with BJZZ. The larger coefficient on the persistent component relative to the residual (0.291% vs. 0.049%) indicates that the observed predictability is primarily attributable to persistent retail flows, while retail trading embeds only a limited amount of information. We normalized all variables and get consistent result that the coefficient on the “other” component is the smallest. Once social media components are introduced in column (2), the explanatory power of the persistent component is substantially attenuated, suggesting that social media amplifies retail trading intensity, generating demand shocks of sufficient magnitude to affect short-term returns.³⁸ This finding is consistent with prior literature (e.g., Gervais et al., 2001; Da et al., 2011; Lou, 2014; Gargano et al., 2018) that attention-grabbing events increase retail buying and subsequent price pressure. Social media plays a significant role in enhancing stock visibility and directing investor attention. Furthermore, heightened Twitter discussion accompanied by positive average sentiment significantly strengthens the positive predictive relation, consistent with our earlier evidence that

³⁸ We do not interpret this result as implying that the persistent component is entirely explained by social media. Some small stocks exhibiting strong persistence do not have social media activity.

return predictability is mainly from intense retail buying as well as with Hu et al. (2021), who document that positive sentiment on WallStreetBets predicts higher subsequent returns. In contrast, column (3) and (4), which correspond to the 2017-2022 period, show that none of the components exhibit significant predictive power. These findings indicate that although social media can amplify short-term retail demand shocks, its ability to generate persistent return predictability diminishes as liquidity improves.

Nevertheless, social media may still play a role in the decay of predictability. To explore whether its influence operates independently of stock size and liquidity, we separately analyze small stocks with low liquidity and other stocks. Table 13, Panel C shows that the positive contributions of both the “other” and social media components are concentrated exclusively among small and illiquid stocks. This finding indicates that, although social media can amplify short-term retail trading predictability under certain conditions, its effect is secondary to the structure characteristics of the underlying stocks. Social media appears to strengthen price impacts only when liquidity is sufficiently low for retail order flow to move prices, rather than serving as an independent source of predictive power.³⁹ Moreover, the “other” component is significant only among small and illiquid stocks, implying that although retail trading may contain some informational content, this information is rapidly incorporated into prices in liquid stocks. Considering that retail investors’ information acquisition may differ between small and large stocks, we further examine small and medium stocks with high liquidity (see Table IA-9), obtaining results consistent with those in Panel C, reinforcing the conclusion that liquidity conditions, rather than information differences, determine the extent to which retail trading translates into predictable returns. Although our analysis relies on Twitter-based measures of social

³⁹ We tried to sort stocks into quartiles based on tweet volume and sentiment, and the results remain consistent.

media, we interpret our results as a lower-bound estimate of the broader influence of social media on retail trading behavior.

[Table 13]

4.3. Determinants of retail trading

We also examine the determinants of retail trading during the 2014-2016 and the 2017-2022 periods to assess whether the changes in the drivers of retail trading help explain the decline in its predictive power. We run a regression where the dependent variable is next-week retail flow imbalance. To assess the persistence of retail flow, we include four lags of retail flow imbalance as independent variable. A high degree of autocorrelation in retail flow imbalance indicates that buying or selling pressure tends to persist over several weeks, generating predictable demand shocks that influence future stock prices. Strong correlations between retail trading and its lags can also reflect herding behavior. As retail investors gain access to more diverse information channels, we might expect reductions in both herding intensity and the autocorrelation of retail flows, thereby weakening its predictive power. We also incorporate several explanatory variables that may shape retail trading decisions: weekly stock returns and turnover, monthly returns, cumulative 6-month returns, and an indicator for lottery-like stocks. A lottery-like stock is defined as one with a below-average price, above-average idiosyncratic volatility, and above-average idiosyncratic skewness in the previous month (Kumar, 2009). Table IA-10 shows that the coefficients on lagged retail flow imbalance are similar across the two subperiods, indicating that the persistence of retail flow has remained largely stable over time and is therefore unlikely to explain the observed decline in predictability. Smaller negative coefficients on weekly and monthly returns points to an increase in contrarian trading among retail investors. However, as shown in the momentum-based sorting results and the decomposition of the contrarian component, this shift does not translate into

meaningful predictive power. Instead, greater contrarian activity is more consistent with retail investors providing liquidity. The coefficient on the lottery-stock indicator declines modestly over time. In unreported analyses, we find no evidence of a structural change in retail investors' preference for lottery-like stocks. Overall, modest variation in some retail trading determinants does not account for the sharp deterioration in retail predictability.

4.4. Abnormal retail flows and increase in less experienced traders

We also examine whether the decline in retail predictability is related to abnormal retail trading. Barber et al. (2024) show that retail trades negatively predict short-term returns when retail volume is unusually high, while retail trades positively predict returns during periods of normal activity. One potential explanation for the decline in predictability is that an increased frequency of abnormal retail trading could offset positive predictive signals and thereby weaken aggregate predictability. To evaluate this mechanism, we apply their standardized abnormal retail volume (SARV) measure to identify stocks with unusually high retail trading activity. In untabulated results, we find no evidence that temporarily elevated retail flows systematically contribute to the deterioration of retail return predictability during the 2017-2022 period. Therefore, abnormal retail trading is unlikely to be a primary driver of the observed decline in predictability.

Another explanation for the decline in predictability is that the influx of less sophisticated retail traders may dilute the informativeness of aggregate retail order flow. Even-Tov et al. (2022) show that commission fee cuts on online trading platforms disproportionately attract inexperienced traders, although they find no corresponding change in retail investor's gross return performance. If such inflows reduce the average information content embedded in retail trading, the predictive power of retail flows should weaken following large retail participation shocks. We

examine retail trading predictability before and after major retail flow shocks. As shown in Figure IA-1, retail flows exhibit two pronounced surges, occurring in 2018 and again in 2020.⁴⁰ These increases coincide with the widespread elimination of brokerage commissions by online trading platforms and the surge in retail participation during the pandemic period, respectively. Prior studies (e.g., Even-Tov et al., 2022; Ozik et al., 2021) and statistics on Robinhood’ new user accounts show that both episodes were driven largely by the entry of relatively inexperienced retail investors. We decompose the daily prediction of retail trading using Eq. (8) over six-months windows before and after each shock. Following BJZZ and our discussion in Section 4.2., we focus on changes in “Other” component, which captures the residual information content in retail trading beyond persistence and contrarian effects. If heightened retail participation dilutes information quality, we would expect a significant decline in the estimated coefficients on the “Other” component in the post-shock periods. However, Table IA-11 shows that the differences in the “Other” coefficients before and after the shocks are not significantly negative for return predictability over the subsequent one- to three-day horizons. These findings indicate that retail flow shocks do not materially reduce the information content of retail trading, consistent with the conclusion of Even-Tov et al. (2022). We further explore potential heterogeneity by examining a subsample of small-cap stocks, where retail participation is typically more pronounced and informational frictions may be more severe. Nevertheless, the results for small stocks closely mirror those of the full sample. Taken together, although retail participation increased substantially following commission reductions and during the pandemic, the associated influx of

⁴⁰ To verify episodes of unusually elevated retail activity observed in Figure IA-1, we model monthly retail flow as a time series and extract its unexpected component. We take the logarithm of retail flow to mitigate skewness and estimate an autoregressive AR(1) specification to capture its normal persistence based on Bayesian Information Criteria. The residuals from this model are interpreted as retail flow shocks. We then compute the rolling three-month sum of positive standardized shocks and classify months in the top decile of this distribution as high-retail-flow periods.

new traders does not appear to have meaningfully diluted the information embedded in retail order flow. Therefore, potential reduction in average trader sophistication is unlikely to provide a sufficient explanation for the post-2016 decline in retail predictability. Importantly, these findings also strengthen the causal interpretation linking improved liquidity to the decline in predictability. Specifically, we find no evidence supporting the reverse causal channel in which an influx of inexperienced retail investors simultaneously reduces return predictability and improves liquidity.

4.5. Macroeconomic factors

We also investigate whether changes in the macroeconomic environment contribute to the observed decline in the predictive power of retail trading. We incorporate several widely used macroeconomic indicators into the VAR system estimated earlier: (i) inflation, measured using the daily 5-year breakeven inflation rate; (ii) the term spread, defined as the yield difference between the 10-year Treasury bond and the 3-month Treasury bill; (iii) the credit spread, computed as the yield difference between Moody's Baa- and Aaa-rated bonds; and (iv) the economic uncertainty proxied by the CBOE Volatility Index (VIX), which reflects the market expectations of near-term volatility implied by S&P 500 option prices. To ensure stationery, we take first differences of all macroeconomic series and verify using augmented Dickey-Fuller tests that the transformed series exhibit no evidence of non-stationarity. We first assess whether the relationship between illiquidity and the retail-based hedged portfolio returns remain robust after controlling for macroeconomic conditions. Table IA-12, Panel A confirms that there is a Granger-causal relation between lagged illiquidity and the retail-based portfolio returns, consistent with Table 9, indicating that their relationship is not significantly affected by macroeconomic fluctuations. Next, we estimate separate VAR models for each macro variable paired with the hedged portfolio returns to examine whether macroeconomic shocks influence the return predictability of retail trading. We find no

statistically significant Granger-causal relationship between lagged macro variables and the long-short portfolio returns, except for the change in the term spread which exhibits a very weak association with a Chi-squared p-value at 0.093. Finally, we examine the joint significance of a VAR system including all four macro variables along with the long-short portfolio returns and the results reveal no significant relationships. Overall, fluctuations in inflation, credit conditions, interest rate structure, and market volatility do not appear to play a significant role in the evolution of retail trading's predictive power.

4.6. Investment and profitability factors

We also test whether retail investors exhibit predictability with respect to the investment and profitability factors in Fama and French's (2015) five-factor model. As reported in Table IA-13 and IA-14, retail flow imbalance shows predictive power for the next-week returns, but the effect does not load meaningfully on different factor exposures. However, when we isolate the subsample of small and low-liquidity stocks, we find that the predictability is concentrated entirely within this group, indicating that these factors do not provide a systematic channel through which retail trading generates return predictability.

Taken together, the results in this section suggest that while several factors contribute to short-term fluctuations in retail trading activity, they do not account for the systematic decline in return predictability, which is more closely linked to improvements in market liquidity.

5. Conclusion

This paper documents a pronounced decline in the predictability of retail trading for future stock returns over the 2014-2022 period and links this decline to changes in stock market liquidity. We find that retail order flow positively predicts returns for up to five weeks during 2014-2016, but this predictive relation disappears in the subsequent 2017-2022 period. Using DGTW

characteristic-adjusted returns and portfolio sorts on size, book-to-market, and momentum, we show that this predictability is concentrated in small, low-liquidity stocks and is largely absent in more liquid firms. During the earlier period, intense retail buying pressure in a subset of small and illiquid stocks is associated with positive, predictable returns. As liquidity improves in the later period, the price impact and persistence of retail-induced demand imbalances diminish, weakening the return predictability.

We provide several pieces of evidence consistent with this mechanism. First, during 2014-2016, the predictability is concentrated in the top quartile of retail flow imbalance and is present only among small stocks with low liquidity, but not among high-liquidity small stocks. Second, portfolio and vector autoregression analyses show that increases in liquidity are associated with a decline in the returns of trading strategies that exploit this predictability. Third, active investors, such as institutional investors and short sellers, can affect the predictability of retail trading as they facilitate the absorption of retail-driven demand imbalances. Fourth, variation in liquidity around Russell index reconstitution provides complementary evidence that retail predictability is affected by changes in liquidity.

These findings indicate that liquidity plays a central role in shaping retail trading predictability in the earlier period and its subsequent erosion. They also suggest that retail trading predictability is more consistent with a friction-based explanation driven by persistent demand imbalances than with superior information embedded in retail trades. While gradual liquidity improvements help explain the longer-term decline, the Tick Size Pilot Program further accelerates the short-term deterioration by sharply reducing retail participation among treated small-cap stocks and weakening retail-driven demand shocks from 2016 to 2017. Finally, although social media

discussions and positive sentiment can stimulate retail trading and amplify short-term price impacts during 2014-2016, their contribution to return predictability in 2017-2022 remains limited.

Importantly, our results do not suggest that retail investors have lost their ability to influence asset prices. Episodes such as Hertz during the 2020 lockdown and GameStop in early 2021 demonstrate that sudden surges in coordinated retail trading can still generate sharp price movements and trigger liquidity spirals. Prior literature (e.g., Barber et al., 2024; Luo et al., 2025; Da et al., 2025) shows that retail trading can exert transitory price pressure when investor attention is intensely focused. However, such effects are episodic and event-driven, and the persistent return predictability observed during 2014-2016 among small and illiquid stocks is far less likely in today's more liquid market environment. Moreover, both theoretical and empirical research (e.g., Collin-Dufresne and Fos, 2015; 2016; Cookson et al., 2022) shows that informed traders strategically increase trading when noise trading intensifies. As retail trading becomes more active and increasingly clusters around salient news events (e.g., Hirshleifer and Sheng, 2022; Farrell et al., 2022), informed traders can more readily identify and exploit retail-driven price pressures, either by riding the trend or trading against temporary mispricing. These dynamics further attenuate the persistence of retail-based predictability.

Overall, our findings highlight the central role of market liquidity in shaping the impact of retail trading on asset prices. For regulators and market designers, policies that affect trading participation or liquidity, such as the TSPP, can materially alter how retail demand is transmitted into prices. For institutional investors, our results highlight the importance of liquidity provision and arbitrage capacity in absorbing retail-driven demand imbalances, particularly in small-cap stocks.

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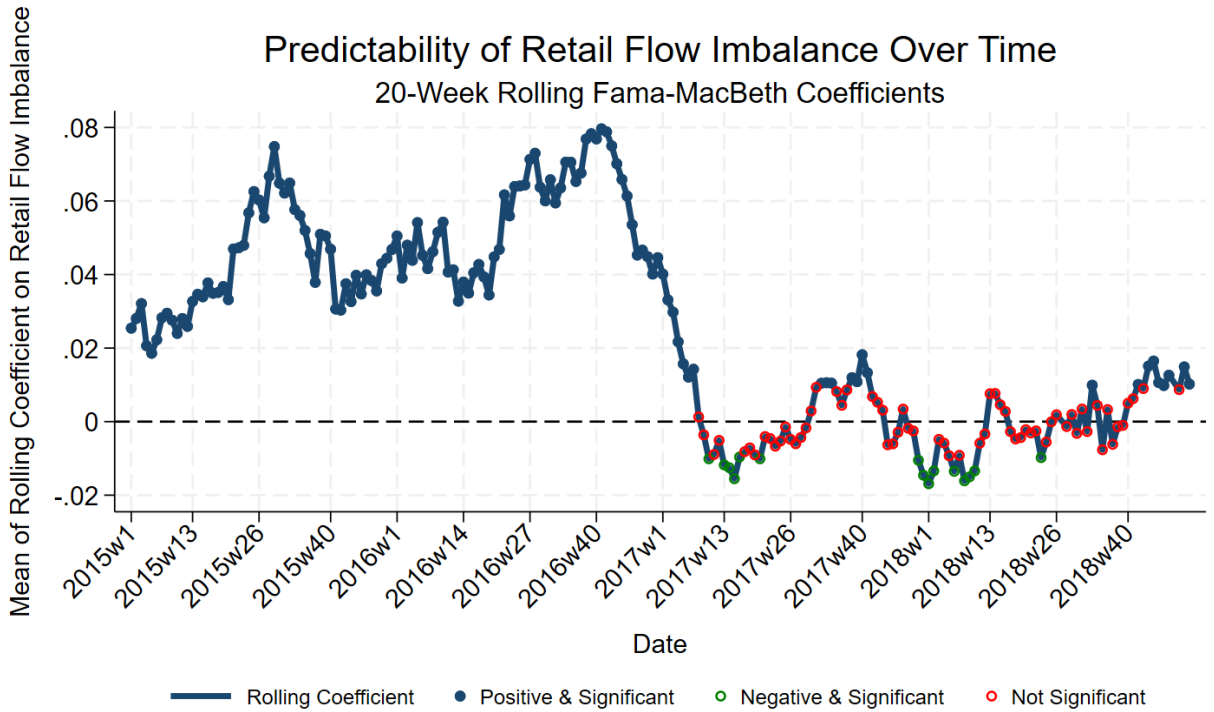
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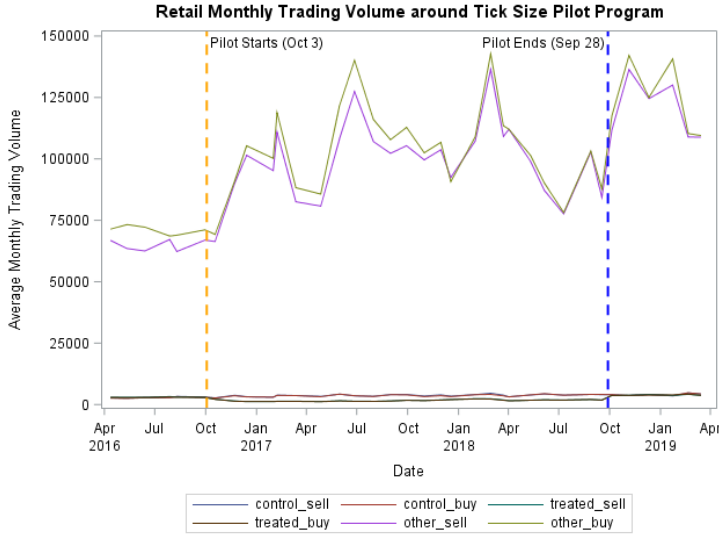
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Figure 1. Predictability of retail trading over time

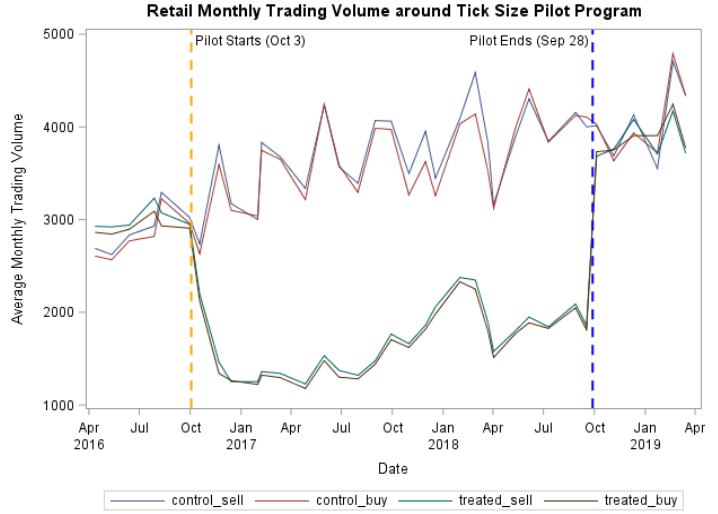


This figure plots 20-week rolling averages of Fama-MacBeth coefficients from weekly cross-sectional regressions of next-week stocks on retail flow imbalance during the 2015-2018 periods. Filled navy circles indicate weeks where the rolling coefficient is statistically positively significant at the 5% level, while hollow red circles indicate weeks where the coefficient is not significant and hollow green circles indicate weeks where the coefficient is statistically negatively significant at the 5% level. Statistical significance is assessed using Newey-West standard errors with 10 lags to account for serial correlation induced by overlapping rolling windows. The dashed horizontal line represents zero. Control variables include current weekly returns and turnover, previous monthly returns and return volatility, and cumulative returns over the prior six months. Monthly return volatility is computed as the standard deviation of daily returns. Turnover is defined as total trading volume divided by total shares outstanding. All coefficient estimates are multiplied by 100. All weekly variables are measured from Wednesday to the following Tuesday.

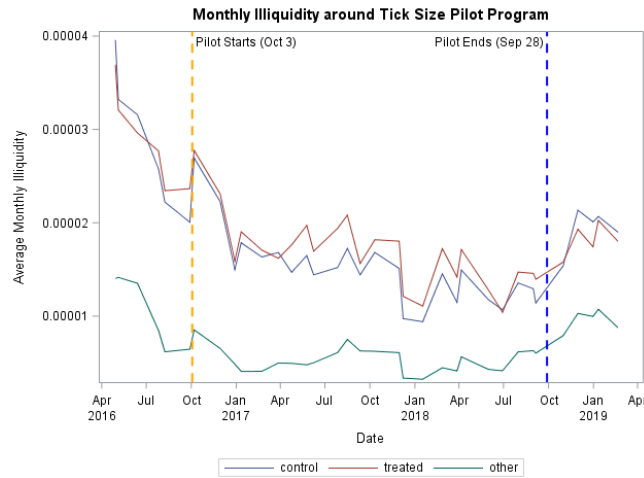
Figure 2. Retail trading activity and the Tick Size Pilot Program



(a)



(b)



(c)

Figure (a) and (b) illustrate monthly retail trading volume, separately for buy and sell activity, around the implementation of the Tick Size Pilot Program across different stock groups. Figure (c) illustrates monthly illiquidity levels for the same groups over the same period. Under the program, the SEC randomly assigned 1,200 small-cap stocks to three treatment groups (pilot stocks) and 1,200 small-cap stocks to a control group. All remaining stocks are classified as “Other” stocks. Figure (a) displays buy and sell trading volumes for all three groups, while Figure (b) focuses on the treated and control group. The horizon axis represents time, while the vertical axis measures retail average monthly trading volume for (a) and (b) and average monthly illiquidity level for (c). The two vertical lines mark the start (October 3rd, 2016) and end (September 28th, 2018) of the program. Following Amihud (2002), monthly illiquidity is computed as the average of the daily ratio of absolute return to dollar trading volume, multiplied by 10^6 . Illiquidity is winsorized at the top and bottom 1%.

Table 1. Summary statistics of retail trading activity and stock characteristics

This table displays summary statistics of retail trading activity and stock characteristics. Panel A reports time-series cross-sectional averages of retail flows and stock characteristics in 2014-2022. The sample covers 2,266 trading days. Turnover is defined as total trading volume divided by total shares outstanding. The daily DGTW return is computed as the stock's return minus the return of its corresponding value-weighted DGTW characteristic portfolio, where portfolios are sorted quarterly. Stocks with minimum prices below \$1 at the previous month-end are excluded from the sample. Panel B reports two normalized measures of retail trading activities: NTA I and NTA II, as well as retail flow imbalance across different stock categories for the two subperiods: 2014-2016 and 2017-2022. NTA I and NTA II are computed using Eq. (1). Stock categories are defined based on the 125 DGTW portfolios. Observations during the COVID-19 shock period (January 2020 – April 2020) are excluded.

Panel A. Summary statistics of retail flows and stock characteristics in 2014-2022					
Variable	Mean	Median	Std Dev	Minimum	Maximum
<i>Mroibflow</i>	-0.005	0.009	0.025	-0.114	0.076
Buy Flow (Millions of \$)	1.151	1.112	0.371	0.317	2.890
Sell Flow (Millions of \$)	1.068	1.037	0.341	0.224	2.651
Turnover (%)	2.105	2.038	0.440	0.550	4.955
Return (%)	0.051	0.083	1.326	-12.267	9.901
DGTW Return (%)	0.041	0.066	1.403	-12.823	10.185
Price (\$)	48.071	47.866	4.745	31.148	60.627
Market Capitalization (Millions of \$)	9,694.410	9,460.973	1,398.090	7,169.440	13,053.290
Number of stocks	2,724.000	2,787	642.739	1,805.000	3,931.000

Panel B. Retail trading activities and factor exposures							
Stock category		2014-2016			2017-2022		
		NTA I	NTA II	<i>Mroibflow</i>	NTA I	NTA II	<i>Mroibflow</i>
Overall		0.039	0.269	-0.019	0.032	0.403	0.003
Size	Small	0.055	0.282	-0.029	0.044	0.540	-0.002
	Big	0.039	0.216	0.006	0.033	0.229	0.020
B/M	Growth	0.043	0.384	-0.009	0.035	0.513	0.010
	Value	0.035	0.235	-0.026	0.031	0.398	0.001
Momentum	Losing	0.032	0.373	-0.022	0.030	0.643	0.008
	Winning	0.047	0.313	-0.014	0.037	0.431	0.003

Table 2. Prediction of retail trading for future stock returns

This table displays the predictability of retail flow imbalance for weekly stock returns during the 2014-2016 and 2017-2022 periods. Panel A reports the predictability for next-week returns, and Panel B reports the predictability for horizons of up to seven weeks. The independent variable is the weekly retail flow imbalance, computed as the cumulative daily imbalances. The dependent variable is the weekly stock returns, measured as the cumulative daily returns. We estimate Fama-MacBeth (1973) regressions and report the time-series averages of the coefficients. All coefficient estimates are multiplied by 100. Control variables include current weekly returns and turnover, previous monthly returns and return volatility, and cumulative returns over the prior six months. Monthly return volatility is computed as the standard deviation of daily returns. Turnover is defined as total trading volume divided by total shares outstanding. All weekly variables are measured from Wednesday to the following Tuesday. Observations during the COVID-19 shock period (January 2020 – April 2020) are excluded from the sample. T-statistics (in parenthesis) are computed using Newey-West standard errors. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Panel A. Prediction of retail flow imbalance for next-week returns				
	2014-2016		2017-2022	
Dependent variable:	Ret (i, w+1)	T-stats	Ret (i, w+1)	T-stats
<i>mroibflow</i> (i, w)	0.045***	(6.60)	0.005	(0.85)
Weekly return (i, w)	-1.237	(-1.48)	-2.162	(-3.81)
Turnover (i, w)	-0.027	(-3.35)	-1.083	(-2.12)
Monthly return (i, m-1)	-0.252	(-0.82)	-0.464	(-1.21)
Monthly return (i, m-7, m-2)	-0.416	(-3.80)	-0.214	(-1.42)
Monthly volatility (i, m-1)	2.086	(0.53)	2.604	(0.62)
Obs.	272,766		564,627	
Adjusted R-squared	0.043		0.026	

Panel B. Prediction of retail flow imbalance for weekly returns at longer horizons						
	2014-2016					
	Ret (i, w+2)	Ret (i, w+3)	Ret (i, w+4)	Ret (i, w+5)	Ret (i, w+6)	Ret (i, w+7)
<i>mroibflow</i> (i, w)	0.026***	0.036***	0.017***	0.026***	0.002	0.007
	(3.26)	(3.85)	(3.05)	(2.60)	(0.32)	(1.01)
	2017-2022					
<i>mroibflow</i> (i, w)	0.009	0.010	0.009	0.008	0.015	0.011
	(0.71)	(0.77)	(0.73)	(0.76)	(1.14)	(1.20)

Table 3. Prediction of retail trading by year

This table summarizes the year-by-year predictability of retail flow imbalance for weekly stock returns over horizons of up to seven weeks. The independent variable is the weekly retail flow imbalance, computed as the cumulative daily imbalances. The dependent variable is the weekly stock return, measured as the cumulative daily return. We estimate Fama-MacBeth (1973) regressions and report the time-series averages of the coefficients on retail flow imbalance. All coefficient estimates are multiplied by 100. Control variables include current weekly returns and turnover, previous monthly returns and return volatility, and cumulative returns over the prior six months. Monthly return volatility is computed as the standard deviation of daily returns. Turnover is defined as total trading volume divided by total shares outstanding. All weekly variables are measured from Wednesday to the following Tuesday. Observations during the COVID-19 shock period (January 2020 – April 2020) are excluded from the sample. T-statistics (in parentheses) are computed using Newey-West standard errors. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Prediction of retail flow imbalance on future weekly returns										
Year	Week 1	Week 2	Week 3	Week 4	Week 5	Week 6	Week 7	Controls	Obs.	Adjusted R-squared
2014	0.022*** (3.30)	0.030*** (3.32)	0.033*** (2.56)	0.020** (2.13)	0.009** (2.40)	-0.001 (-0.22)	-0.005** (-1.99)	Yes	86,123	0.047
2015	0.045*** (3.67)	0.035* (1.85)	0.023* (1.71)	0.018* (1.87)	0.033** (2.44)	0.012** (2.28)	-0.005 (-0.53)	Yes	91,523	0.039
2016	0.060*** (5.79)	0.021** (2.05)	0.052*** (3.66)	0.025** (2.22)	0.016 (1.65)	-0.004 (-0.20)	0.014 (1.54)	Yes	95,347	0.043
2017	-0.000 (-0.04)	0.011 (1.13)	-0.008 (-1.04)	-0.004 (-0.70)	-0.001 (-0.07)	-0.013 (-0.81)	0.009 (1.53)	Yes	102,672	0.030
2018	-0.000 (-0.08)	-0.013 (-1.56)	-0.007 (-0.74)	0.016 (1.47)	-0.009 (-1.24)	-0.015 (-1.50)	-0.005 (-0.87)	Yes	104,219	0.033
2019	-0.012 (-1.03)	-0.003 (-0.26)	-0.030** (-2.07)	0.001 (0.09)	-0.016* (-1.82)	0.014 (0.60)	-0.012* (-1.94)	Yes	110,760	0.038
2020	0.008 (0.35)	0.026 (1.46)	-0.002 (-0.05)	0.103 (1.36)	0.065 (1.35)	0.038 (1.26)	0.026 (0.77)	Yes	76,749	0.045
2021	0.013 (0.88)	0.026 (0.85)	0.010 (0.78)	0.017 (1.07)	0.005 (0.60)	0.030** (2.31)	0.009 (0.72)	Yes	138,533	0.063
2022	0.003 (0.12)	-0.028 (-1.12)	0.014 (0.60)	-0.016 (-1.16)	0.016 (1.08)	0.032 (1.41)	0.017 (1.51)	Yes	142,834	0.058

Table 4. Decompositions of retail trading and prediction for weekly returns

This table displays the predictability of retail flow imbalance quartiles for weekly stock returns over the next five weeks during the 2014-2016 period (Panel A) and 2017-2022 period (Panel B). Stocks are sorted each week into quartiles based on retail flow imbalance: bottom 25% (strongest selling), bottom 25% - bottom 50%, top 50% - top 25%, and top 25% (strongest buying). The independent variables are interactions between retail flow imbalance and the quartile indicators. The dependent variable is the weekly return. We estimate Fama-MacBeth (1973) regressions and report the time-series averages of the quartile coefficients. All coefficient estimates are multiplied by 100. Control variables include current weekly returns and turnover, previous monthly returns and return volatility, and cumulative returns over the prior six months. Monthly return volatility is computed as the standard deviation of daily returns. Turnover is defined as total trading volume divided by total shares outstanding. All weekly variables are cumulated from Wednesday to the following Tuesday. Observations during the COVID-19 shock period (January 2020 – April 2020) are excluded from the sample. T-statistics (in parentheses) are computed using Newey-West standard errors. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Panel A. Prediction of retail flow imbalance quartiles in the 2014-2016					
	Dependent variable: Ret (i, w+k)				
	w+1	w+2	w+3	w+4	w+5
<i>mroibflow</i> (i, w, B25%)	0.113*	0.078	0.037	0.003	-0.005
	(1.94)	(1.11)	(0.55)	(0.05)	(-0.07)
<i>mroibflow</i> (i, w, B25%-B50%)	0.124	0.173	0.138	0.181	0.090
	(1.30)	(1.84)	(1.19)	(0.89)	(1.12)
<i>mroibflow</i> (i, w, T50%-T25%)	-0.061	-0.057	0.034	0.002	-0.146
	(-0.44)	(-0.71)	(0.30)	(0.01)	(-1.34)
<i>mroibflow</i> (i, w, T25%)	0.041***	0.019*	0.034***	0.020**	0.025***
	(4.64)	(1.86)	(3.23)	(2.36)	(2.64)
Controls	Yes	Yes	Yes	Yes	Yes
Obs.	272,766	270,459	268,920	267,348	265,093
Adjusted R-squared	0.048	0.041	0.038	0.038	0.038
Panel B. Prediction of retail flow imbalance quartiles in the 2017-2022					
	Dependent variable: Ret (i, w+k)				
	w+1	w+2	w+3	w+4	w+5
<i>mroibflow</i> (i, w, B25%)	0.003	0.014	0.001	-0.0007	0.000
	(0.03)	(0.20)	(0.01)	(-0.08)	(-0.01)
<i>mroibflow</i> (i, w, B25%-B50%)	-0.123	-0.130	0.127	0.146	0.116
	(-0.52)	(-0.72)	(0.57)	(0.76)	(0.85)
<i>mroibflow</i> (i, w, T50%-T25%)	-0.040	0.003	0.031	-0.167	-0.268***
	(-0.26)	(0.02)	(0.22)	(-1.65)	(-2.82)
<i>mroibflow</i> (i, w, T25%)	0.006	0.008	0.011	0.012	0.008
	(0.65)	(0.61)	(0.70)	(0.58)	(0.70)
Controls	Yes	Yes	Yes	Yes	Yes
Obs.	564,627	562,485	560,355	558,226	556,096
Adjusted R-squared	0.054	0.050	0.044	0.046	0.044

Table 5. Prediction of retail trading for DGTW returns

This table displays the predictability of retail flow imbalance quartiles for weekly stock returns over the next five weeks during the 2014-2016 period (Panel A) and 2017-2022 period (Panel B). Each week, stocks are sorted into quartiles based on their weekly retail flow imbalance: bottom 25% (strongest selling), bottom 25% - bottom 50%, top 50% - top 25%, and top 25% (strongest buying). The independent variables are interaction terms between retail flow imbalance and the quartile indicators. The dependent variable is the weekly DGTW return, computed as the cumulative daily return minus the cumulative daily return of the stock's corresponding value-weighted DGTW portfolio, where portfolios are rebalanced quarterly. We estimate Fama-MacBeth (1973) regressions and report the time-series averages of the quartile coefficients. All coefficient estimates are multiplied by 100. Control variables include current weekly returns and turnover, previous monthly returns and return volatility, and cumulative returns over the prior six months. Monthly return volatility is computed as the standard deviation of daily returns. Turnover is defined as total trading volume divided by total shares outstanding. All weekly variables are measured from Wednesday to the following Tuesday. Observations during the COVID-19 shock period (January 2020 – April 2020) are excluded from the sample. T-statistics (in parentheses) are computed using Newey-West standard errors. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Panel A. Prediction of retail flow imbalance quartiles for future DGTW returns in the 2014-2016					
	Dependent variable: DGTW Ret (i, w+k)				
	w+1	w+2	w+3	w+4	w+5
<i>mroibflow</i> (i, w, B25%)	0.139** (2.49)	0.068 (1.21)	0.059 (1.27)	0.024 (0.52)	0.009 (0.19)
<i>mroibflow</i> (i, w, B25%-B50%)	0.105 (1.07)	0.009 (1.17)	0.007 (0.07)	0.156 (1.79)	0.0081 (1.01)
<i>mroibflow</i> (i, w, T50%-T25%)	0.109 (0.70)	-0.044 (-0.67)	0.222 (0.81)	-0.010 (-0.06)	-0.107 (-1.01)
<i>mroibflow</i> (i, w, T25%)	0.037*** (5.14)	0.011 (1.28)	0.019 (1.57)	0.007 (0.98)	0.017* (1.79)
<i>mroibflow</i> (i, w)	0.040*** (6.33)	0.010 (1.20)	0.021** (2.12)	0.009 (1.48)	0.018 (1.39)
Controls	Yes	Yes	Yes	Yes	Yes
Obs.	272,766	270,459	268,920	267,348	265,093
Adjusted R-squared	0.025	0.029	0.025	0.026	0.026

Panel B. Prediction of retail flow imbalance quartiles for future DGTW returns in the 2017-2022

	Dependent variable: DGTW Ret (i, w+k)				
	w+1	w+2	w+3	w+4	w+5
<i>mroibflow</i> (i, w, B25%)	0.105 (1.40)	0.022 (0.43)	0.002 (0.03)	0.008 (0.14)	0.043 (0.49)
<i>mroibflow</i> (i, w, B25%-B50%)	-0.257 (-1.12)	-0.100 (-0.58)	0.162 (0.68)	0.100 (0.44)	0.229 (1.10)
<i>mroibflow</i> (i, w, T50%-T25%)	-0.005 (-0.04)	-0.071 (-0.47)	0.001 (0.01)	-0.089 (-0.97)	-0.200*** (-2.80)
<i>mroibflow</i> (i, w, T25%)	-0.002 (-0.19)	0.008 (0.59)	0.014 (1.25)	0.016 (1.36)	0.006 (0.57)
<i>mroibflow</i> (i, w)	0.001 (0.15)	0.009 (0.80)	0.020 (1.46)	0.014 (1.58)	0.011 (1.56)
Controls	Yes	Yes	Yes	Yes	Yes
Obs.	564,627	562,485	560,355	558,226	556,096
Adjusted R-squared	0.027	0.026	0.025	0.034	0.033

Table 6. Prediction of retail trading conditioning on size and liquidity

Panel A displays the predictability of the top quartile of retail flow imbalance for small, medium, and large stocks over the next five weeks during the 2014-2016 and 2017-2022 periods. Stocks are classified into three size categories based on quarterly DGTW size portfolio rankings. Small stocks correspond to size portfolios “1” or “2”. Medium stocks fall into portfolio “3”. Large stocks correspond to portfolios “4” or “5”. We then construct three interaction terms between the top quartile of retail flow imbalance and these size indicators: Top 25% *mroibflow**Small, Top 25% *mroibflow**Medium, and Top 25% *mroibflow**Large. The remaining three interactions between *mroibflow* and its quartile indicators are retained in the Fama-MacBeth (1973) regressions. The dependent variable is the weekly return controlled for book-to-market and momentum characteristics, computed as the cumulative daily return minus the cumulative daily return of the stock’s corresponding DGTW B/M-Momentum portfolio. All coefficient estimates are multiplied by 100. Control variables include current weekly returns and turnover, previous monthly returns and return volatility, and cumulative returns over the prior six months. Monthly return volatility is computed as the standard deviation of daily returns. Turnover is defined as total trading volume divided by total shares outstanding. All weekly variables are measured from Wednesday to the following Tuesday. Panel B reports time-series cross-sectional averages of illiquidity for small stocks and for the full sample in the 2014-2016 and 2017-2022 periods. Following Amihud (2002), weekly illiquidity is computed as the average of the daily ratio of absolute return to dollar trading volume, multiplied by 10^6 . Illiquidity is winsorized at the top and bottom 1%. Panel C displays the predictability of the top quartile of retail flow imbalance conditional on both firm size and liquidity during the 2014-2016 period. Stocks are sorted into high- and low-liquidity groups based on quarterly illiquidity levels, and corresponding indicator variables are created. We then generate six interaction terms by combining the top quartile of *mroibflow* with size categories (Small, Medium, Large) and liquidity indicators (High, Low). Control variables and the remaining *mroibflow* interactions are identical to those in Panel A. Observations during the COVID-19 shock period (January 2020 – April 2020) are excluded from the sample. T-statistics (in parentheses) are computed using Newey-West standard errors. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Panel A. Prediction of the top quartile of retail flow imbalance conditional on size

Dependent variable: Ret-B/M-MOM (i, w+k)					
2014-2016					
	w+1	w+2	w+3	w+4	w+5
T25% <i>mroibflow</i> *Small	0.042*** (4.65)	0.026** (2.07)	0.039*** (3.34)	0.023*** (2.55)	0.025*** (2.72)
T25% <i>mroibflow</i> *Medium	0.014 (0.37)	-0.082* (-1.90)	0.002 (0.04)	-0.046 (-1.44)	-0.038 (-1.16)
T25% <i>mroibflow</i> *Large	-0.043 (-0.73)	-0.016 (-0.34)	-0.035 (-0.67)	-0.063 (-1.53)	-0.036 (-0.70)
Controls	Yes	Yes	Yes	Yes	Yes
Obs.	272,568	271,615	271,585	266,622	262,019
Adjusted R-squared	0.036	0.034	0.031	0.031	0.032
2017-2022					
	w+1	w+2	w+3	w+4	w+5
T25% <i>mroibflow</i> *Small	-0.003 (-0.25)	0.006 (0.43)	0.005 (0.34)	0.014 (0.69)	0.008 (0.68)
T25% <i>mroibflow</i> *Medium	0.018 (0.49)	0.025 (0.57)	-0.035 (-0.78)	-0.013 (0.69)	0.010 (0.34)
T25% <i>mroibflow</i> *Large	0.001 (0.01)	0.040 (0.63)	0.005 (0.08)	-0.007 (-0.12)	0.032 (0.42)
Controls	Yes	Yes	Yes	Yes	Yes
Obs.	564,627	562,485	560,355	558,226	556,096
Adjusted R-squared	0.039	0.038	0.037	0.037	0.036

Panel B. Summary statistics of illiquidity

2014-2016						
	Number of periods	Mean	Median	Std Dev	Minimum	Maximum
Small stocks	156	80.115	70.690	39.070	23.841	245.201
Total	156	45.756	39.776	21.924	13.976	137.870
2017-2022						
Small stocks	307	34.064	29.813	24.093	4.412	122.995
Total	307	19.867	17.384	13.966	2.619	71.549

Panel C. Prediction of the top quartile of retail flow imbalance conditional on size and liquidity in the 2014-2016

	Dependent variable: Ret-B/M-MOM (i, w+k)				
	w+1	w+2	w+3	w+4	w+5
T25% <i>mroibflow</i> *Small *High	-0.005 (-0.06)	0.046 (0.53)	-0.132** (-2.28)	-0.166 (-1.59)	-0.018 (-0.18)
T25% <i>mroibflow</i> *Small *Low	0.042*** (4.47)	0.019** (1.99)	0.040*** (3.29)	0.024** (2.26)	0.022** (2.25)
T25% <i>mroibflow</i> *Medium *High	-0.020 (-0.35)	-0.146** (-2.21)	-0.011 (-0.26)	-0.061 (-1.61)	-0.004 (-0.09)
T25% <i>mroibflow</i> *Medium *Low	0.048 (0.93)	-0.046 (-0.94)	0.002 (0.04)	0.008 (0.11)	-0.049 (-1.08)
T25% <i>mroibflow</i> *Large *High	-0.052 (-0.90)	-0.044 (-1.02)	-0.044 (-0.84)	-0.037 (-0.85)	-0.061 (-1.39)
T25% <i>mroibflow</i> *Large *Low	-0.344 (-1.23)	-0.148 (-0.57)	-0.285 (-1.04)	-0.005 (-0.03)	0.198 (0.83)
Controls	Yes	Yes	Yes	Yes	Yes
Obs.	272,568	271,615	271,585	266,622	262,019
Adjusted R-squared	0.035	0.034	0.030	0.031	0.031

Table 7. Prediction of retail trading for small stocks with low liquidity

This table displays the predictability of retail flow imbalance for future stock returns conditional on stock type over the next five weeks during the 2014-2016 period. We define two stock-type indicators: *SL*, which equals one for small-cap stocks with low liquidity, identified using quarterly DGTW size portfolios and the Amihud (2002) illiquidity measure, and *Other*, which equals one for all remaining stocks. The dependent variable is the weekly return controlled for book-to-market characteristics, computed as the cumulative daily return minus the cumulative daily return of the stock's DGTW B/M portfolio. Retail flow imbalance is decomposed into quartiles: bottom 25% (strongest selling), bottom 25% - bottom 50%, top 50% - top 25%, and top 25% (strongest buying). The independent variables consist of eight interaction terms that combine the four quartile-based interactions of *mroibflow* with the *SL* and *Other* indicator variables. We also report the aggregate effect of retail flow imbalance conditional on stock type by interacting *mroibflow* with the *SL* and *Other* indicator variables. All coefficient estimates are multiplied by 100. Control variables include current weekly returns and turnover, previous monthly returns and return volatility, and cumulative returns over the prior six months. Monthly return volatility is computed as the standard deviation of daily returns. Turnover is defined as total trading volume divided by total shares outstanding. All weekly variables are measured from Wednesday to the following Tuesday. T-statistics (in parentheses) are computed using Newey-West standard errors. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Prediction of retail flow imbalance conditional on size and liquidity in the 2014-2016					
Dependent variable: Ret-B/M (i, w+k)					
Independent variables	w+1	w+2	w+3	w+4	w+5
<i>mroibflow</i> (i, w, B25%) *SL	0.170** (2.49)	0.065 (0.89)	0.002 (0.03)	0.028 (0.36)	-0.087 (-1.22)
<i>mroibflow</i> (i, w, B25%) *Others	0.115 (1.52)	0.110 (1.44)	0.044 (0.76)	0.176 (1.27)	0.127 (1.29)
<i>mroibflow</i> (i, w, B25%-B50%) *SL	-0.032 (-0.17)	0.019 (0.11)	0.041 (0.23)	-0.044 (-0.23)	0.022 (0.12)
<i>mroibflow</i> (i, w, B25%-B50%) *Others	0.313 (1.48)	0.370 (1.54)	0.163 (1.11)	0.255 (1.01)	0.221 (1.29)
<i>mroibflow</i> (i, w, T50%-T25%) *SL	0.303 (0.99)	0.185 (0.80)	0.631 (1.49)	0.188 (0.35)	0.770 (0.95)
<i>mroibflow</i> (i, w, T50%-T25%) *Others	-0.062 (-0.34)	-0.102 (-0.92)	-0.212* (-1.69)	-0.260* (-1.75)	-0.350 (-1.60)
<i>mroibflow</i> (i, w, T25%) *SL	0.039*** (4.50)	0.019** (1.99)	0.039*** (3.12)	0.022** (2.15)	0.022** (2.27)
<i>mroibflow</i> (i, w, T25%) *Others	0.006 (0.24)	-0.015 (-0.59)	-0.012 (-0.46)	-0.042* (-1.79)	-0.006 (-0.20)
<i>mroibflow</i> (i, w) *SL	0.042*** (5.94)	0.024*** (3.12)	0.039*** (3.43)	0.022*** (2.74)	0.021** (2.12)
<i>mroibflow</i> (i, w) *Others	0.033 (1.62)	0.010 (0.49)	0.006 (0.27)	-0.000 (0.00)	0.008 (0.29)
Controls	Yes	Yes	Yes	Yes	Yes
Obs.	272,568	271,615	271,585	266,622	262,019
Adjusted R-squared	0.039	0.035	0.031	0.031	0.032

Table 8. Retail flow imbalance and weekly portfolio performance, subsample analysis

This table displays the time-series cross-sectional averages of portfolio returns over the next five weeks, sorted by retail flow imbalance during the 2014-2016 period. Stocks are classified into two groups: small stocks with low liquidity (SL) and other stocks based on quarterly DGTW size portfolios and the Amihuid (2002) illiquidity measure. Each week, both groups are independently sorted into deciles based on retail flow imbalance. Portfolio P10 comprises stocks experiencing the strongest retail buying relative to selling, while Portfolio P1 comprises those with the strongest retail selling relative to buying. The P10-P1 spread represents the zero-investment long-short strategy. The return difference is defined as the return from going long the zero-investment strategy among SL stocks and short the corresponding strategy among other stocks. Ret-B/M denotes the weekly return controlled for the book-to-market characteristics, computed as the stock return minus the return of its corresponding DGTW B/M portfolio. All Weekly variables are calculated as the cumulative daily returns from Wednesday to the following Tuesday. All returns are expressed in percentages. T-statistics are reported in parentheses. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Future weekly stock returns sorted on retail flow imbalance in the 2014-2016								
Weekly returns	Small stock with low liquidity			Other stocks			Return difference	Number of periods
	P10	P1	P10-P1	P10	P1	P10-P1		
Ret-B/M (i, w+1)	0.3115*** (2.89)	-0.1376 (-1.21)	0.4491*** (5.79)	0.0751 (0.76)	-0.0480 (-0.05)	0.1231 (1.56)	0.3260*** (3.53)	156
Ret (i, w+1)	0.3158*** (2.68)	-0.1211 (-1.08)	0.4369*** (5.64)	0.0930 (0.93)	-0.0224 (-0.23)	0.1154 (1.61)	0.3215*** (3.50)	156
Ret-B/M (i, w+2)	0.1955* (1.85)	0.0298 (0.39)	0.1657** (2.21)	0.1129 (1.08)	0.0232 (0.24)	0.0897 (1.02)	0.0760 (0.68)	156
Ret (i, w+2)	0.1851* (1.74)	0.0374 (0.33)	0.1477** (2.00)	0.1272 (1.29)	0.0253 (0.25)	0.1019 (1.16)	0.0458 (0.43)	156
Ret-B/M (i, w+3)	0.2514** (2.33)	0.0084 (0.08)	0.2431*** (3.39)	0.0346 (0.38)	0.0165 (0.18)	0.0181 (0.25)	0.2250** (2.29)	156
Ret (i, w+3)	0.2636** (2.47)	0.0160 (0.16)	0.2476*** (3.21)	0.0527 (0.57)	0.0161 (0.17)	0.0367 (0.50)	0.2109** (2.18)	156
Ret-B/M (i, w+4)	0.1791* (1.73)	0.0400 (0.45)	0.1391* (1.88)	-0.0224 (-0.27)	-0.0441 (-0.46)	0.0217 (0.31)	0.1174 (1.28)	156
Ret (i, w+4)	0.1871* (1.89)	0.0443 (0.53)	0.1428** (1.98)	-0.0137 (-0.16)	-0.0435 (-0.44)	0.0298 (0.41)	0.113 (1.24)	156
Ret-B/M (i, w+5)	0.1262 (1.17)	-0.0324 (-0.39)	0.1586** (2.13)	0.0790 (0.96)	0.0120 (0.12)	0.0670 (0.87)	0.0916 (1.03)	156
Ret (i, w+5)	0.1121 (0.98)	-0.0443 (-0.41)	0.1564** (2.01)	0.1089 (1.28)	0.0130 (0.13)	0.0960 (1.22)	0.0604 (0.68)	156

Table 9. VAR: illiquidity and predictability of retail trading

This table reports the results of the VAR model examining the joint dynamics of stock illiquidity and the weekly returns of the long-short portfolio, where returns are controlled for the book-to-market characteristics. The analysis is conducted separately for the subsample of small stocks and for the full sample of all stocks. Each week, stocks are sorted into deciles based on weekly retail flow imbalance. The top decile comprises stocks experiencing the strongest retail buying relative to selling, while the bottom decile comprises those with the strongest retail selling relative to buying. The hedged portfolio is defined as the return of an equal-weighted long-short strategy that is long the top-decile portfolio and short the bottom-decile portfolio. Illiquidity series is measured as the value-weighted weekly Amihud (2002) illiquidity measure. The VAR is estimated with two lags, selected based on the Schwarz Bayesian Information Criterion. We report the cumulative coefficients for the two-lag specifications and the corresponding p-values from F-tests assessing their joint significance. All coefficient estimates are multiplied by 100. The final column presents Chi-squared p-values from Granger-causality Wald tests based on the estimated VAR system. We also report t-statistics from augmented Dickey-Fuller tests for the hedged portfolio returns and the illiquidity series. Observations during the COVID-19 shock period (January 2020 – April 2020) are excluded from the sample. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Impact of illiquidity on the predictability of retail flow imbalance			
Small stocks			
	Cumulative coefficient	F-test p-value	Chi-squared p-value
Dependent variable: hedged portfolio returns			
Illiquidity	0.440***	0.000	0.000
Dependent variable: Illiquidity			
Hedged portfolio returns	32.955	0.635	0.747
t-statistics of Dicker fuller test	Hedged portfolio returns: -21.69		Illiquidity: -9.35
All stocks			
	Cumulative coefficient	F-test p-value	Chi-squared p-value
Dependent variable: hedged portfolio returns			
Illiquidity	1.537***	0.000	0.000
Dependent variable: Illiquidity			
Hedged portfolio returns	23.959	0.670	0.824
t-statistics of Dicker fuller test	Hedged portfolio returns: -21.30		Illiquidity: -10.11

Table 10. Institutional trading, short interest, and retail predictability

This table reports the predictability of retail flow imbalance for future stock returns across different stock types. Panel A classifies stocks using two indicator variables: *SLT* and *Other*. *SLT* equals one for small-cap stocks with low or declining ownership by transient institutional investors, as defined using quarterly DGTW size portfolios and Bushee’ institutional investor classification. *Other* equals one for all remaining stocks. Weekly retail flow imbalance is interacted with each stock-type indicator. The dependent variable is the weekly return controlled for the book-to-market characteristics. Panel B constructs two analogous indicators: *SLS* and *Other*. *SLS* equals one for small-cap stocks with low or declining short-interest percentage. Short-interest percentage is computed as shares sold for short divided by total shares outstanding. The regression specification mirrors that of Panel A. Control variables include current weekly returns and turnover, previous monthly returns and return volatility, and cumulative returns over the prior six months. We estimate Fama-MacBeth (1973) regressions and report the time-series averages of coefficients. T-statistics (in parentheses) are computed using Newey-West standard errors. All weekly variables are measured from Wednesday to the following Tuesday. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Panel A. Prediction of retail flow imbalance conditional on size and transient investor ownership in 2014 – 2016					
	Dependent variable: Ret-B/M (i, w+k)				
	w+1	w+2	w+3	w+4	w+5
<i>mroibflow</i> (i, w) *SLT	0.061*** (6.18)	0.030*** (3.97)	0.067*** (3.67)	0.029*** (3.13)	0.022* (1.69)
<i>mroibflow</i> (i, w) *Others	0.034*** (3.61)	0.009 (1.17)	0.007 (0.74)	0.012 (1.23)	0.009 (1.10)
Controls	Yes	Yes	Yes	Yes	Yes
Obs.	267,480	262,919	261,616	260,996	256,030
Adjusted R-squared	0.040	0.039	0.036	0.036	0.036
Panel B. Prediction of retail flow imbalance conditional on size and short-interest percentage in 2014 – 2016					
<i>mroibflow</i> (i, w) *SLS	0.065*** (6.00)	0.028*** (3.19)	0.044*** (2.68)	0.021** (2.30)	0.027** (2.25)
<i>mroibflow</i> (i, w) *Others	0.021** (2.05)	0.012 (1.13)	0.009 (0.90)	0.011 (1.61)	0.012 (1.19)
Controls	Yes	Yes	Yes	Yes	Yes
Obs.	256,635	249,578	241,557	232,607	221,880
Adjusted R-squared	0.043	0.042	0.039	0.039	0.040

Table 11. The Russell index reconstitution, liquidity, and retail predictability

This table examines the relation between Russell 3000 reconstitution, stock liquidity, and retail trading predictability. Panel A estimates the effects of index entry and exit on weekly stock illiquidity. Considering the limited number of observations near the Russell 3000 cutoff, we analyze the full sample period from 2014-2022. Russell Inc. reconstitutes its indexes on the last Friday of June each year based on end-of-May market capitalization rankings, with index composition remaining fixed until the subsequent reconstitution (i.e., within a cohort year, defined as the period from one June reconstitution to the next). For index entry, we consider stocks within a cohort year that experience inclusion, while for index exit, we focus on those that experience exclusion. *Entry* (or *Exit*) equals one for observations after June in the cohort year and zero otherwise. Control variables include current-week returns and turnover, previous monthly returns, return volatility, market capitalization and book-to-market ratio, and cumulative returns over the prior six months. Regressions include stock and year-week fixed effects, with standard errors are double-clustered at the stock and year-week levels. Panel B examines the predictability of retail flow imbalance for next-week stock returns conditional on Russell 3000 reconstitution during the 2014 – 2022 period. The dependent variable is weekly return controlled for book-to-market characteristics. The independent variables are retail flow imbalance and its interaction with *Entry* or *Exit* indicator. The coefficient on *mroibflow* captures the predictive effect when the stocks remain outside (*Entry*=0) or inside (*Exit*=0) the index. The interaction terms represent the changes in predictability following entry or exit. When *Entry* (*Exit*) equals one, the predictive effect is given by the sum of the coefficient on *mroibflow* and its interaction, capturing the retail predictability after a stock is added to (excluded from) the index. Control variables, fixed effects, and clustered standard errors follow Panels A, except for the book-to-market ratio that has been controlled in the dependent variable. All weekly variables are measured from Wednesday to the following Tuesday. Observations during the COVID-19 shock period (January 2020 – April 2020) are excluded from the sample. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Panel A. Inclusion to Russell 3000 and illiquidity in 2014 – 2022				
Dependent variable: weekly illiquidity				
Variables	Index entry		Index exit	
	Coefficient	t-statistics	Coefficient	t-statistics
Entry	-0.173***	(-3.00)		
Exit			0.157***	(2.66)
Weekly return	-0.184	(-2.17)	-0.108	(-2.64)
Turnover	-0.087	(-0.49)	-0.193	(-1.38)
Monthly return	-0.070	(-2.01)	-0.028	(-0.71)
Prior 6-month	-0.034	(-2.40)	-0.021	(-1.18)
Return volatility	-0.930	(-1.08)	-0.295	(-0.39)
Market capitalization	-0.120	(-1.93)	-0.043	(-0.70)
B/M	0.074	(1.62)	0.019	(0.66)
Stock, Year-Week FE		Yes		Yes
Obs.		36,898		64,498
Adjusted R-squared		0.204		0.293

Panel B. Prediction of retail flow imbalance on next-week returns conditional on the Russell index reconstitution in 2014 – 2022

Dependent variable: Ret-B/M (i, w+k)				
	Index entry		Index exit	
	Coefficient	t-statistics	Coefficient	t-statistics
<i>mroibflow</i> (i, w) *Entry	-0.059**	(-2.14)		
<i>mroibflow</i> (i, w) *Exit			0.092**	(2.55)
<i>mroibflow</i> (i, w)	0.050**	(2.16)	-0.044**	(-1.48)
Entry the Russell 3000	-0.009	(-0.54)		
Exit the Russell 3000			0.048***	(2.90)
Controls		Yes		Yes
Stock, Year-Week FE		Yes		Yes
Obs.		35,500		62,360
Adjusted R-squared		0.064		0.044

Table 12. Retail trading and the Tick Size Pilot Program

This table reports the predictability of retail flow imbalance for future stock returns across different stock groups over the next three weeks during the pre-, during-, and post-Tick Size Pilot Program (TSPP) periods. The US Securities and Exchange Commission (SEC) implemented the TSPP on October 3, 2016, and terminated it on September 28, 2018. Under the program, the SEC randomly assigned 1200 small-cap stocks to three treatment groups (pilot stocks) and 1200 small-cap stocks to a control group. All remaining stocks are classified as “Other” stocks. The pre-TSPP period spans January 1, 2014 to October 2, 2016, while the post-TSPP period covers September 29, 2018 to December 31, 2022. The coefficients labeled Pre – During represent the differences between the pre-TSPP and TSPP periods, and the coefficients labeled Post – During represent the differences between the post-TSPP and TSPP periods. Control variables include current-week returns and turnover, previous monthly returns and return volatility, and cumulative returns over the prior six months. Monthly return volatility is computed as the standard deviation of daily returns. Turnover is defined as total trading volume divided by total shares outstanding. All weekly variables are measured from Wednesday to the following Tuesday. T-statistics (in parentheses) are computed using Newey-West standard errors. Observations during the COVID-19 shock period (January 2020 – April 2020) are excluded from the sample. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Prediction of retail flow imbalance on weekly returns across groups									
Dependent variable: Ret-B/M (i, w+k)									
	Treated small stock			Control small stock			Other stocks		
	w+1	w+2	w+3	w+1	w+2	w+3	w+1	w+2	w+3
Pre-TSPP	0.043*** (5.31)	0.025** (2.19)	0.027** (2.19)	0.025*** (2.57)	0.023** (2.22)	0.028** (2.28)	0.032* (1.72)	0.021 (1.07)	0.007 (0.22)
During-TSPP	-0.002 (-0.26)	-0.002 (-0.22)	-0.003 (-0.37)	0.030** (2.49)	0.011 (0.81)	0.015 (1.29)	-0.031 (-0.83)	0.012 (0.40)	-0.016 (-0.87)
Post-TSPP	0.018 (1.23)	0.042 (1.38)	0.010 (0.43)	0.025* (1.69)	0.015 (0.92)	-0.004 (-0.24)	0.022 (0.80)	0.027 (0.83)	0.035 (1.02)
Pre – During	0.050*** (4.02)	0.029** (2.12)	0.030* (1.70)	-0.008 (-0.72)	0.019 (1.11)	0.016 (0.95)	0.063 (1.53)	0.009 (0.26)	0.022 (0.65)
Post – During	0.020 (1.13)	0.046 (1.46)	0.008 (0.29)	-0.008 (-0.44)	0.010 (0.48)	-0.018 (-0.82)	0.057 (1.23)	0.015 (0.35)	0.059 (1.57)

Table 13. Social media and prediction of retail trading

This table displays summary statistics for the social media variables derived from Twitter and the decomposition of predictability of retail trading for the 2015-2016 and 2017-2022 periods. Panel A presents summary statistics for weekly tweet counts and average sentiment. Weekly variables are computed as the means of daily observations from Wednesday through the following Tuesday. Positive (negative) sentiment values indicate that of positive (negative) tone dominates in tweets. Panel B reports the decomposition of the predictive power of retail flow imbalance for next-week stock returns. We estimate two-stage Fama-MacBeth (1973) regressions in which retail flow imbalance is decomposed into five components as defined in Eq. (8). The *Persistence* component, capturing price pressure, is estimated in the first stage using past flow imbalance. The *Contrarian* component is estimated using past returns (previous week, previous month, and cumulative returns over the prior six months). The *Social media* component is estimated using weekly average sentiment and the tweet-volume percentile. To mitigate the disproportionate allocation of Twitter discussions across firm size, we sort firms into deciles by market capitalization and compute each stock’s daily tweet count percentile within its respective size group. Tweet-volume percentiles are then split into high (above 50th percentile) and low (below 50th percentile), and sentiment into positive and negative categories. The social media component is then interacted with these four indicator variables. The residual from the first-stage estimation is labeled as “*Other*”, which can be attributed to other information about future returns held by retail investors. Panel C reports the decomposition separately for small stocks with low liquidity and for other stocks during 2015-2016. Control variables include current-week returns and turnover, previous monthly returns and return volatility, book-to-market ratio, and cumulative returns over the prior six months. Monthly return volatility is computed as the standard deviation of daily returns. Turnover is defined as total trading volume divided by total shares outstanding. T-statistics (in parentheses) are computed using Newey-West standard errors. Observations during the COVID-19 shock period (January 2020 – April 2020) are excluded from the sample. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Panel A. Summary statistics of tweets publication counts and sentiments								
Tweet publication counts								
Period	Mean	Median	Std Dev	Min	Max	Obs.		
2015-2016	64.745	16.000	418.679	0.000	45,563.000	128,400		
2017-2022	56.828	14.800	387.135	0.000	83,405.000	527,472		
Tweets sentiment								
Period	Mean	Median	Std Dev	Min	Max	% of positive obs.	% of negative obs.	Obs.
2015-2016	0.041	0.013	0.136	-1.000	1.000	70.554%	29.446%	128,400
2017-2022	0.027	0.001	0.138	-1.000	1.000	63.092%	36.908%	527,472

Panel B. Decomposition of prediction of retail flow imbalance in 2015-2016

	2015-2016		2017-2022	
	Dependent variable: Ret-B/M (i, w+k)			
	(1)	(2)	(3)	(4)
Persistence	0.291** (2.41)	0.157 (1.04)	0.063 (0.76)	-0.126 (-0.96)
Contrarian	2.368 (1.12)	3.107 (1.07)	-1.017 (-0.97)	-0.410 (-1.20)
Other	0.049*** (5.69)	0.043*** (3.46)	0.001 (0.25)	0.001 (0.15)
Social media*Positive*High		2.723*** (3.73)		-0.339 (-0.58)
Social media*Positive*Low		1.033 (1.14)		-0.331 (-0.54)
Social media*Negative*High		-0.888 (-0.80)		0.607 (0.62)
Social media*Negative*Low		2.753 (1.53)		0.154 (0.22)
Controls	Yes	Yes	Yes	Yes
Obs.	185,553	126,219	681,533	453,111
Adjusted R-squared	0.046	0.053	0.048	0.054

Panel C. Decomposition of prediction of retail flow imbalance in 2015-2016

	Dependent variable: Ret-B/M (i, w+k)			
	Small stocks with low liquidity		Other stocks	
	(1)	(2)	(3)	(4)
Persistence	0.308*** (2.65)	0.024 (0.19)	0.152 (0.48)	0.245 (1.07)
Contrarian	0.015 (0.91)	3.613 (1.08)	0.048 (1.34)	4.403 (1.08)
Other	0.047*** (5.43)	0.037*** (3.05)	0.033 (1.15)	0.041 (1.41)
Social media*Positive*High		4.206*** (3.09)		1.209 (1.42)
Social media*Positive*Low		2.185 (1.22)		0.058 (0.06)
Social media*Negative*High		-2.529 (-1.11)		0.240 (0.22)
Social media*Negative*Low		2.791 (0.91)		2.461 (1.54)
Controls	Yes	Yes	Yes	Yes
Obs.	71,233	52,604	93,213	72,151
Adjusted R-squared	0.042	0.049	0.089	0.103