Retail Investors and Stock Return Predictability

Darius Palia [a], Joakim Westerholm [b], and Pramod Kumar Yadav [b]

January 2026

Abstract

We study whether retail trading predicts stock returns using a complete dataset comprising of all equity transactions over the period 1997-2022**.** Unlike prior research that relies on brokerage accounts or retail trade classification algorithms, our data on Finnish households captures the **complete market, for a long period of time, explicitly identifies retail investors and whether the trade is a buy or sell order**. We find that the average aggregate retail order flow forecasts stock returns over horizons up to 15 weeks; retail investors tend to trade contrarian to past returns, and the predictive content of their trades arises mainly from persistent order flow and information not captured by observable public news. Exploiting investor-level identifiers, we show that return predictability varies systematically across investor types. Predictability is higher among local investors, working-age investors (particularly those aged 26-40), more sophisticated investors, and men, while being weaker or absent for distant, older, and less sophisticated investors. These results demonstrate substantial heterogeneity in the economic magnitude of retail investors' ability to predict returns**,** as demographic and economic differences shape how household activity contributes to price discovery.

---

[a] Rutgers Business School, and [b] University of Sydney Business School, respectively. We thank Azi Ben-Raphael, Sophia Li, Tavy Ronen, Mehrdad Samadi and seminar participant at Rutgers for helpful comments and discussions. All errors remain our responsibility. Corresponding author: Darius Palia, dpalia@business.rutgers.edu

I. Introduction

Retail investors are increasingly important participants in modern stock markets, both in terms of trading volume and their influence on price formation. Their presence has grown markedly in recent times, with surges during episodes such as the COVID-19 pandemic highlighting the role of retail flows in driving prices (Welch, 2022). Yet, the academic literature remains divided on whether retail trading predicts returns and, if so, at what horizon, and why? One strand of literature[1] finds retail traders to be informed, reflecting private signals and/or superior processing of public news (Kelley and Tetlock, 2013; Fong, Gallagher, and Lee, 2014). According to the informed retail trader hypothesis, a large buy order imbalance would suggest a positive relationship with both short-term and long-term return predictability. Another strand of literature suggests that retail orders are autocorrelated due to order splitting to minimize the price impact of each trade. In turn, risk averse market makers raise prices for adverse selection and/or inventory reasons, which results in a positive relationship between buy order imbalances and short-term returns. This relationship turns to zero or negative in the long-term (Chordia and Subrahmanyam, 2004; Dorn, Huberman, and Sengmuller, 2008). The third strand of literature argues that the positive relation between retail order flow and future short-term stock returns arises from compensation for liquidity provision (Kaniel, Saar, and Titman, 2008; Barrot, Kaniel, and Sraer, 2016). Finally, a strand of literature finds that retail traders are noise traders with limited return predictability at both the short-term and long-term horizons (Odean, 1998; Barber and Odean, 2000, 2008; Hvidkjaer, 2008; Barber, Odean, and Zhang, 2008).

In an influential paper,[2] Boehmer, Jones, Zhang, and Zhang (2021, henceforth BJZZ) advanced this literature by proposing an algorithmic methodology on sub-penny prices of market orders to identify and sign retail trades that are reported to one of FINRA's Trade

[1] See Section 2 of this paper for a detailed explanation of these papers.

[2] Battalio et al. (2024) identify 28 papers that use BJZZ's algorithmic methodology which are published or forthcoming in the top finance and accounting journals as of February 2024.

Reporting Facilities. Using data from 2010 to 2015, they find that retail order imbalance predicts the cross-section of stock returns, providing large-scale empirical evidence that retail activity contributes to price formation. However, the BJZZ algorithmic methodology has been shown to have limitations – it identifies only a subset of retail trades; misclassifies institutional trades as retail trades; often incorrectly classifies buy and sell orders; and results from the algorithm are weak or disappear in the post-BJZZ sample period. These shortcomings, emphasized by Battalio et al. (2024), Barber et al. (2024), and Ardia, Aymard, and Cenesizoglu (2024) have raised concerns about the external validity of BJZZ's findings, and left open the question of whether the predictability of the average retail trader is a general phenomenon or an artifact of mismeasurement.

Despite the competing results of the papers above, all the empirical evidence has come from proprietary or small datasets (brokerage-level data covering narrow investor segments), or algorithmic classifications of identifying retail traders — which makes it difficult to draw broad conclusions about the impact of retail investors in price discovery.

To address the above concerns, we use a unique data set which has several advantages. First, we observe the entire universe of daily retail trades in Finland, rather than a partial or algorithmically inferred subset. Second, investor identity is provided by the central clearinghouse itself (along with their postal address), and the central clearinghouse also specifies whether each trade is a buy or sell order. This eliminates any measurement error coming from algorithmic methodologies to identify and sign retail trades. Third, our panel data set is long, spanning 26 years (1997–2022), which allows us to evaluate the stability of results over time and to revisit recent concerns that retail predictability has weakened/disappeared in the post-BJZZ period (Ardia, Aymard, and Cenesizoglu, 2024). Finally, and importantly, our data allow us to disaggregate retail investors into heterogeneous groups — by location, age, sophistication, and gender. Such heterogeneity is not easily available in most other datasets on

retail trading. Together, these features enable us to provide a comprehensive assessment of whether retail trading predicts stock returns, and which types of investors drive any observed predictability effects, and through which channel.

This paper contributes to the existing literature by answering the following questions.

1) Do retail investors as a group predict stock returns, when we can accurately identify who is defined as a retail trader for all market participants, and know the precise direction of every trade (i.e., buy or sell)? Additionally, we examine if the retail trader's stock return predictability is only over the short-term, or is it more-long term?

2) If we find that retail investors can predict stock returns over the long-term, we then examine what is driving their predictability ability? Liquidity, price-pressure, and/or information?

3) Are all retail traders the same in their ability to predict long term stock returns? Accordingly, we examine for differences in the ability of retail traders to predict future stock returns between local and distant retail investors, retail investors of different age groups, sophisticated and naive retail investors, and male and female retail investors, respectively.

4) Finally, we examine if the above relationships stay constant over time, or vary across periods?

To answer the first question above, we examine whether aggregate buying and selling of retail investors predicts stock returns. We find that retail investors in aggregate tend to buy after prices decrease, and sell after prices increase, at a weekly horizon. This contrarian trading pattern of retail investors with respect to past returns is consistent with several papers (Kaniel, Saar, and Titman, 2008; Kelley and Tetlock, 2013; Barrot, Kaniel, and Sraer, 2016). We find that the cross-section of weekly retail order imbalances predicts stock returns over the next week, consistent with the findings in BJZZ. When we examine longer horizons, we find that

retail order imbalances continue to predict future weekly stock returns up to 15 weeks. The predictive power is also observed for 15-week cumulative returns. These results suggest that the return predictability of the retail traders as a group is more long term in nature and not mean reverting. The long-term predictability is consistent with an information-based explanation.

To understand the nature of information embedded in retail trades, we distinguish between retail investors' ability to process public information and their potential to act on information not immediately reflected in prices. If retail investors are skilled at processing public news, their trading should covary with contemporaneous news surprises, and such news-based trading should predict future returns to the extent that markets underreact to public information. Alternatively, if retail investors possess information beyond observable public news, through local knowledge, private signals, or superior interpretation of firm fundamentals, return predictability should arise independently of measured news and persist over time.

To empirically distinguish between these channels, we adopt the two-stage decomposition methodology of BJZZ. This methodology separates retail order imbalance into various components associated with persistence, contrarian trading, public news sentiment, and a residual component orthogonal to these forces. In the first stage, we find that retail order flow is persistent, contrarian with respect to past returns, and responsive to contemporaneous public news surprises. In the second stage, however, return predictability is primarily driven by persistence and the residual component, while contrarian and public-news-based trading contribute little. These findings suggest that retail return predictability is unlikely to arise from liquidity provision or short-lived price pressure and is instead consistent with an information-based explanation in which information enters prices gradually through sustained trading, rather than through immediate reactions to observable public news.

To address questions two and three above, we examine whether our results are different for different types of retail traders. We begin by asking whether the aggregate retail order flow's predictive power stems from a small subset of traders with potentially distinct information or expertise. Specifically, we identify the personal trades of company insiders and employees of financial institutions (whom we refer to as brokers). Because such traders are relatively few and trade infrequently, their order flows are not suitable for stand-alone tests of return predictability. Instead, we ask whether excluding their trades from aggregate retail order imbalance alters our main results. We find that retail return predictability remains essentially unchanged, indicating that the predictive content of retail order flow is not driven by insider or broker activity.

Beyond insiders and brokers, heterogeneity across households has long been central to household finance. Prior work shows that demographic and economic characteristics such as age, income, and location shape participation, portfolio choice, and investment performance (Guiso and Sodini, 2013; Korniotis and Kumar, 2011; Gomes, Haliassos, and Ramadorai, 2021). Betermier et al. (2025) further demonstrate that variation in household characteristics can help explain cross-sectional expected returns in equilibrium, highlighting how investor heterogeneity matters for asset pricing more broadly. Jones et al. (2025) show that return predictability of retail order flow in the Chinese stock market is not uniform: trades by higher account size predict returns, whereas those by smaller-account investors do not. This evidence suggests that demographic and economic differences across investors may translate into differences in trading motives and price impact. Our data allow us to extend this insight to the entire market by studying heterogeneity in retail order flow along four key dimensions—location, age, sophistication, and gender—and testing whether return predictability is concentrated among particular investor groups.

We first examine heterogeneity by investor location, classifying trades as local or more distant based on the geographic proximity between investors and the firm. Specifically, we sort trades into terciles based on the investor-firm distance and construct weekly retail order flow separately for each group. We find that weekly order flow from local investors significantly predicts the cross-section of stock returns, whereas return predictability in the two more distant groups is relatively modest. In terms of economic magnitude, a one-interquartile range increase in local order imbalance is associated with a 0.71% increase in 15-week cumulative returns. While prior research on investor location has emphasized portfolio choice and investment performance (Coval and Moskowitz, 2001; Ivković and Weisbenner, 2005), our evidence suggests that geography also matters for aggregate order flow and its predictive power for returns.

The second characteristic we examine is investor age. We categorize retail investors into five groups: (i) 25 years or younger, (ii) 26–40 years, (iii) 41–55 years, (iv) 56–68 years, and (v) older than 68, with the last cutoff chosen to align with the upper bound of the retirement age in Finland. We construct retail order flow for each group and examine their ability to predict returns. We find that return predictability varies systematically across age groups and is concentrated among working-age investors. Specifically, order imbalances for investors aged 25 or younger, 26–40, 41–55, and 56-68 are associated with economically and statistically significant return predictability, with the strongest effects observed for the 26-40 group. An interquartile-range increase in weekly order imbalance for this group corresponds to a 1.10% increase in 15-week cumulative stock returns. By contrast, trading by investors past retirement age exhibits no predictive power. This pattern is broadly consistent with findings that older investors trade less effectively (Korniotis and Kumar, 2011).

The third dimension of heterogeneity we examine is investor sophistication. We consider two proxies for investor sophistication. First, our data provide information on the Euro

value of investor accounts for the period September 2000 to January 2012, which we use as a proxy for financial sophistication -- as wealthier investors are reasonably expected to have greater access to information and resources. Specifically, investors are classified into three groups based on their beginning-of-month account balance: those in the top group are considered sophisticated, those in the bottom group are classified as naïve, and those in the middle group intermediate. We find that return predictability decreases as we move from the high-account-balance group to the low-account-balance group.

As a second proxy for financial sophistication, we classify investors residing in the greater Helsinki area as more sophisticated, reflecting the concentration of financial institutions and high-skilled occupations in Finland's main financial center. As this proxy is based on investors' place of residence rather than proximity to the traded firm, it captures financial sophistication rather than local information advantages. Using this proxy, we find that return predictability is concentrated in the order imbalance of Helsinki-based investors.

The fourth dimension of heterogeneity we examine is gender. We separately construct weekly retail order flow for men and women and test their predictive power both individually and jointly. When estimated separately, order imbalances for both men and women significantly predict future returns. However, when entered jointly in predictive regressions, only male order flow retains statistical significance. Because men account for a larger fraction of total trading volume in our data and male and female order flows are highly correlated, male order flow dominates in joint specifications. In terms of magnitude, an interquartile-range increase in male order imbalance is associated with a 0.91% increase in 15-week cumulative stock returns, compared to 0.38% for female order imbalance. Related work by Barber and Odean (2001) documents gender differences in trading intensity and portfolio outcomes, rather than the information content of trades.

Finally, we find no evidence of a structural decline in the cross-sectional predictive power of retail order imbalances. In all three subperiods, the pre-BJZZ period (1997–2009), the BJZZ period (2010–2015), and the post-BJZZ period (2016–2022), the coefficient on retail order imbalance remains positive and statistically significant.

This paper is organized as follows. Section II provides a brief description of the Finnish stock market and a detailed explanation of the related literature. Section III describes our data and the empirical variables constructed for our tests. We present our empirical findings in Section IV for retail investors defined as a homogeneous group, whereas Section V presents our empirical findings for different types of retail investors. Section VI examines the stability over time of our main results, and Section VII provides our conclusions.

II. Section II

In this section we briefly describe trading activities on Finland's stock exchange called Nasdaq Helsinki (formerly the Helsinki Stock Exchange), and a detailed explanation of the related academic literature.

II. A Nasdaq Helsinki

Finnish common stocks trade on Nasdaq Helsinki, a part of the Nasdaq Nordic and Baltics Exchange, which forms an integrated network of exchanges across Northern Europe. Trading is conducted electronically in a centralized limit order book, consistent with the structure of most European equity exchanges.

Panel A of Table 1 compares total equity trading value across major exchange groups in 2022. The total value traded in the NYSE and US Nasdaq in 2022 is about US $40 trillion. The corresponding value in Nasdaq Nordic and Baltics Exchange is Euro 1 trillion. Given the prominent role of the U.S. stock market in global portfolios, the Nordic market's smaller scale is expected. The traded value in the Nordic market is comparable to that in the German market.

*** Table 1 ***

The average number of Finnish stocks traded per day during our sample is 121 compared to 3000 stocks in the U.S. market. The average daily volume in the Finnish market is 65 million shares whereas the corresponding figure for U.S. Nasdaq is 2.5 billion shares.

Panel B of Table 1 reports average trade size at selected benchmark years for Nasdaq Helsinki and the U.S. Nasdaq. Average execution size declines sharply in both markets between 2002 and 2022, consistent with the broader shift toward electronic and algorithmic trading. While execution sizes differ in levels, the magnitude of the decline is comparable across the two markets.

Despite its relatively small size, the Finnish stock market is economically relevant for global investors. Over the sample period, foreign investors hold, on average, approximately 60% of total market capitalization. Nokia has the largest market capitalization on the exchange, with 45.5% held by global institutional investors during our sample period. Furthermore, foreign ownership was widespread, with most common stocks having foreign ownership exceeding 1%. These features make the Finnish market informative for studying trading behavior in an exchange-centric environment with substantial institutional participation.

II. B Related Literature

Our paper is related to the existing literature in many different contexts. We contribute to three strands of literature. First, our paper contributes to the extensive literature on retail trading and stock returns. Prior studies have relied on proprietary datasets covering subsets of the retail investor universe, such as U.S. brokerage accounts (Barber and Odean, 2000, 2008), French brokerage data (Barrot, Kaniel, and Sraer, 2016), Australian trading records (Fong, Gallagher, and Lee, 2014), and Finnish account-level data (Linnainmaa, 2010), or algorithmically inferred retail trades (BJZZ and papers adopting their classification). More recently, Jones et al. (2025) study retail trading in China, while Laarits and Sammon (2025)

emphasize retail "habitat" effects. Related work shows that although retail investors trade against anomaly-based expected returns on average, short-horizon retail trade imbalances still predict realized returns at monthly horizon in ways largely orthogonal to those expected returns (McLean, Pontiff, and Reilly, 2025). Compared to these studies, we exploit the full universe of retail trades in Finland, which allows us to document market-wide evidence that retail order flow predicts cross-sectional returns, measured without the sampling limitations or algorithmic classification errors that affect many of the prior papers.

Second, our analysis highlights the importance of investor heterogeneity in retail order flow. Prior studies often treat retail traders as a homogeneous group, even though theory suggests differences in information, motives, and constraints across investor types. We show that the predictive content of retail order flow is concentrated among specific subsets of retail investors, indicating heterogeneity plays a central role in how retail trading affects prices. These results complement recent work using household holdings data. Balasubramanyam et al. (2024) document how investor characteristics shape the cross-section of retail holdings, while Betermier et al. (2025) show that wealth and age help explain expected returns in equilibrium. Our finding that working-age investors' trades predict returns differs from Betermier et al. (2025), who emphasize older investors' portfolio holdings in explaining risk premia. This reflects distinct levels of analysis: their evidence is based on expected returns in long-term portfolio holdings and risk premia, whereas we study stock return predictability in retail trades. Together, these results suggest that investor heterogeneity matters not only for participation and portfolio choice, but also for how retail trading aggregates into price formation.

Third, our paper sheds light on the mechanisms through which retail order flow predicts returns. Prior studies have proposed three competing explanations, including liquidity provision (Kaniel, Saar, and Titman, 2008), temporary price pressure from persistent flows (Chordia and Subrahmanyam, 2004), and informed trading (Kelley and Tetlock, 2013; BJZZ,

2021). Using the decomposition framework of BJZZ (2021), we show that return predictability in our setting is primarily driven by persistence in retail order flow and by informed trading, with little contribution from contrarian liquidity provision. These findings suggest that the predictive power of retail trades is not merely a behavioural artifact but instead reflects the ability of some subsets of retail investors to incorporate information into prices.

III. Data and Empirical Variables

Our retail trading data source is from Euroclear Finland Ltd. (formerly Finnish Central Securities Depository) that maintains daily comprehensive official records of share ownership and trades at the individual investor account level. The dataset is for the 26-year period (January1997 to December 2022) and comprises all traded Finnish stocks. All relevant data is adjusted for stock splits and has already been converted from the local Finnish currency (Markka) to Euros.

For each investor account, we observe every single transaction made by the account, ISIN of transaction (stock identifier), transaction date, transaction type (buy v. sell), number of shares traded, and investor characteristics such as year of birth, age, gender, and postal code. We retrieve stock characteristics (stock price, returns, and accounting information) from Compustat Global and Data Stream. We merge individual-level account data with Compustat Global and Data Stream using ISIN. Given our research question, we construct our baseline sample at stock-date level by aggregating all retail transactions into buys and sells. Our final sample with non-missing stock characteristics comprises of 551,648 stock-date observations, in 283 unique common stocks listed on the Nasdaq Helsinki Exchange.

Retail order imbalance: Following BJZZ, we construct two measures of retail order imbalance for each stock i on day t for every retail account. The first proxy is based on the volume of shares $oibvol_{i,t}$, and the second proxy for is $oibtrd_{i,t}$ which is based on the number of trades. They are calculated as follows.

$$oibvol_{i,t} = \frac{bvol_{i,t} - svol_{i,t}}{bvol_{i,t} + svol_{i,t}}$$

$$oibtrd_{i,t} = \frac{btrd_{i,t} - strd_{i,t}}{btrd_{i,t} + strd_{i,t}}$$

where $bvol_{i,t}$ refers to the volume of shares bought by retail investors; $svol_{i,t}$ refers to the volume of shares sold by retail investors; $btrd_{i,t}$ refers to the number of buy trades by retail investors; and $strd_{i,t}$ refers to the number of sell trades by retail investors, respectively. Note that the second order imbalance measure does not depend on the size of orders placed and helps us disentangle the impact of the size of the trade on our results. In other words, if we find the same results for both proxy variables, the size of the order is not significantly impacting our results.

The summary statistics for the order imbalance measures are given in Table 2. Across stock-days, retail investors, on average, buy 45,082 shares and sell 42,581 shares. The average number of buy trades is around 55 trades, and the average number of sell trades is around 40 trades. The volume-based order imbalance has a mean of -0.01 and a standard deviation of 0.437, suggesting that on average, retail buys offset retail sales. The 25th and 75th percentiles are -0.25 and 0.23 respectively, suggesting a sizable cross-sectional variation in the volume-based order imbalance. The mean order imbalance for trade is 0.044 with a standard deviation of 0.378. This measure also exhibits sizable cross-sectional variation in retail trading activity. The correlation between the two order imbalance measures is around 81%. Our summary statistics are broadly consistent with those reported in BJZZ.

*** Table 2 ***

IV. Empirical Tests and Results for Retail Investors as a Homogeneous Group

Consistent with BJZZ, we conduct our main analysis on weekly or longer horizons to reduce microstructure noise. We construct our main trading variable as firm-level order imbalances over five-day (weekly) intervals. Specifically, we aggregate daily observations of retail order imbalances into overlapping 5-day rolling windows, constructing daily cross-sections of 5-day (weekly) retail order flow imbalances.

IV. A Determinants of Retail Order Imbalances

We start our empirical analysis by examining whether retail trading is persistent and how it responds to past price movements. To test this, we implement Fama and MacBeth's (1973) two-stage estimation. In the first stage, each trading day, we estimate the following cross-sectional regression:

$$oib_{i,w} = b0_w + b1_w oib_{i,w-1} + b2'_w X_{i,w-1} + u1_{i,w} \quad (1)$$

where $oib_{i,w}$ is weekly order imbalance for firm *i* during week *w,* from *day* 1 to *day* 5. The key explanatory variable is the firm's weekly order imbalance from the previous week (*day* -4 to *day* 0). To capture potential momentum or reversal effects, we include firm *i*'s returns during week *w-1*, previous month, and the previous six months. Following BJZZ, we also control for return anomalies such as size (log market cap), value (log book-to-market), log turnover, and daily return volatility, each computed over the previous month.

From the first stage, we obtain a time series of regression coefficients $\{b0_w, b1_w, b2'_w\}$. We use these coefficients to conduct statistical inference in the second stage. Because the dependent variable and key regressors are constructed from overlapping five-day windows, the resulting coefficient estimates are serially correlated. We therefore adjust standard errors following Newey and West (1987).

The regression results are reported in Table 3. In the first column where we use volume-based order imbalance as the dependent variable, the coefficient on past week order imbalance is 0.45 with a t-stat of 107. Controlling for past returns and return anomalies in columns (2-3) decreases the coefficient on past order imbalance slightly. The magnitude and statistical significance of the coefficient suggests that retail trades are persistent on a weekly basis in our sample. A similar pattern is observed in BJZZ. Turning to past returns, we observe negative and statistically significant sensitivities at all horizons, suggesting that retail trading exhibits a pronounced contrarian component. The coefficients for past week, past month, and past six months returns in column 3 are -1.78 (t-stat =-16), -0.97 (t-stat =-19), and -0.26 (t-stat =-15) respectively, indicating that retail investors buy recent losers and sell recent winners. In terms of control variables, retail order flow is tilted towards smaller firms, growth firms, and stocks with higher volatility and turnover. Similar patterns are observed when we use trade-based order imbalance as the dependent variable.

*** Table 3 ***

Taken together, our finding suggests that retail traders tend to buy stocks that have recently performed poorly and sell those that have recently performed well, indicating a contrarian pattern that persists over horizons from one week to six months. The weekly and monthly contrarian patterns observed in our sample are consistent with findings in BJZZ, Barrot, Kaniel, and Sraer (2016), and Kaniel, Saar, and Titman (2008).

IV.B Retail Order Imbalance and Short-Term Stock Returns

In this section, we examine whether retail investors contribute to price discovery in the short run (one-week ahead). Specifically, we ask whether retail order imbalance can predict the cross-section of short-term stock returns. To test this, we adopt Fama and MacBeth's (1973) two-stage estimation. In the first stage, for each trading day, we estimate the following predictive cross-sectional regression:

$$ret_{i,w} = d0_w + d1_w oib_{i,w-1} + d2'_w X_{i,w-1} + u2_{i,w} \quad (2)$$

where $ret_{i,w}$ is weekly return for firm i during week w and $oib_{i,w-1}$ is the previous week's retail order imbalance. As in BJZZ, the control variables are returns over the previous week, month, and six months, and the return anomalies (log market cap, log book-to-market, log turnover, and daily return volatility), each measured over the previous month.

From the first stage, we obtain daily time-series of regression coefficients $\{d0_w, d1_w, d2'_w\}$. We conduct statistical inference on these coefficients in the second stage. Because of overlapping daily frequency data for weekly order imbalances and returns, we adjust the time-series standard errors following Newey and West (1987).

A significantly positive $d1_w$ indicates that stocks attracting net buying (selling) from retail investors tend to perform better (worse) than the cross-sectional average next week. Such a pattern may arise from persistent price pressure, liquidity provision, or from retail investors trading on information. A negative and statistically significant $d1_w$ would be consistent with short-term noise trading by retail investors. Finally, a statistically insignificant $d1_w$ would suggests that, on average, retail order flow is largely uninformative for future stock returns.

The estimation results for predictive equation (2) are reported in Table 4. In the first column, when we include $oib_{i,w-1}$, measured as past week's order imbalance using volume of shares, as the sole independent variable, the coefficient on $oib_{i,w-1}$ is 0.0010 (t-stat = 7). In column (2), we add past return controls which reduces the coefficient on $oib_{i,w-1}$ to 0.0007 (t-stat = 5.1). The positive and statistically significant $d1_w$ indicates that retail order imbalance predicts the cross-section of one-week ahead stock returns in the same direction. For example, stocks that experience net retail selling in a given week earn significantly lower returns in the following week.

It is possible that retail investors trade on return anomalies that are associated with superior future returns. Under such a scenario, predictive power of retail trades may capture exposure to these anomalies. To address this, we augment our specification with these anomalies used by BJZZ and report the results in the third column. This reduces the coefficient on $oib_{i,w-1}$ to 0.0006 (t-stat = 4.63) and increases the average adjusted R^2 from 0.072 to 0.123. We estimate the economic magnitude of this effect by multiplying the interquartile range of the variable (past week's order imbalance) with the regression coefficient and report it at the bottom of the table. For example, moving from the 25th percentile to the 75th percentile of $oib_{i,w-1}$ results in a weekly difference of 0.093% (=0.000626*1.574, 4.84% per year) in the next week stock return.

We continue to find a positive and statistically significant $d1_w$ in the last three columns where we use number of trades-based order imbalance. The economic magnitude in column (6) is 0.115% (5.75% per year). The obtained predictability using number of trades-based order imbalance suggests that our results are not driven by trade size.

*** Table 4 ***

When we look at the control variables, we find that past week return loads negatively, indicating short-term reversal -- whereas past month and past six months returns load positively, indicating momentum. The coefficients on size and daily return volatility are negative, whereas the coefficient on turnover is positive. The average adjusted R^2 from the first-stage cross-sectional estimation with the full set of control variables are around 12%. In subsequent analyses, we use the full specification including past returns and return anomalies as controls.

Taken together, these results indicate that the average retail order flow is informative about the cross-section of stock returns over short horizons.

IV.C Retail Order Imbalance and Long-Term Stock Returns

The evidence so far shows that retail order imbalance predicts future stock returns over the next week. We next examine whether the return predictability persists over longer horizons. This will allow us to distinguish whether the observed predictability we found above is transient or persistent. If return predictability reverses or dissipates quickly, it would suggest that retail trades reflect short-term noise that is subsequently corrected. In contrast, persistence in the predictive power would suggest that the average retail investors trades on information that is gradually incorporated into prices.

To test this conjecture, we modify the Fama and MacBeth's equation (2) to examine whether one week of retail order imbalance predicts weekly stock returns at longer horizons:

$$ret_{i,w+k-1} = d0_{w+k-1} + d1_{w+k-1} oib_{i,w-1} + d2'_w X_{i,w-1} + u2_{i,w+k-1} \quad (3)$$

where $ret_{i,w+k-1}$ is the stock *i*'s one-week return during week *w*+*k*. For example, for *k*=2, $ret_{i,w+k-1}$ is calculated as a 5-day return over days *d*+6 to *d*+10. We estimate equation (3) separately for k=1, 2, … 15 to examine how the coefficient $d1_{w+k-1}$ varies with the forecast horizon. A reversal or rapid decline in the coefficient would suggest that the observed predictability is short-lived. In contrast, statistically significant coefficients over longer horizons would indicate persistent return predictability.

We report estimation results for equation (3) in Table 5. For volume-based order imbalance, the coefficients on $oib_{i,w-1}$ are positive and statistically significant across horizons. The estimated coefficient declines gradually from 0.0006 at the one-week horizon to approximately 0.0004 at the fifteen-week horizon. More importantly, we do not observe significant reversal at any value of *k*. The results are similar when we use number of trades-

based order imbalance. Overall, these patterns suggest that the observed return predictability of the average retail investor is long-term (15-week).

*** Table 5 ***

The long-horizon predictive power of retail order flow documented above raises the question of whether its information content translates into economically meaningful return predictability over longer holding periods. We therefore examine whether retail order imbalance also predicts cumulative stock returns over longer horizons. Specifically, we modify the Fama-MacBeth regression in equation (3) by replacing the dependent variable with the cumulative stock returns over a holding horizon of one to fifteen weeks, while using the same set of explanatory variables:

$$ret_{i,w:w+k-1} = d0_w + d1_w oib_{i,w-1} + d2'_w X_{i,w-1} + u2_{i,w:w+k-1} \quad (4)$$

We examine whether retail order imbalance predicts 15-week cumulative stock returns by reporting estimation results for equation (4) in Table 6. The estimated coefficient on volume-based order imbalance is 0.0069 under the full specification. An increase of one interquartile range of $oib_{i,w-1}$ is associated with an increase of 1.085% in 15-week cumulative stock returns. The results are similar when order balance is measured using the number of trades in the last two columns. Our results suggest that the average retail trader makes information-based trades.

*** Table 6 ***

To examine how the predictive power of retail trades evolves across different holding periods, we plot $d1_w$, the estimated coefficient on order imbalance, together with 95% confidence intervals in Figure 1. Graph A uses cumulative stock returns from next week (w) to week 15 (w+14). The coefficients for both volume-based and trade-based order imbalance are positive and increase steadily with the holding period, with no evidence of reversal at longer

horizons. This pattern suggests that retail order imbalance is associated with economically meaningful buy-and-hold return predictability over several weeks.

*** Figure 1 ***

A potential concern is that one-week predictability documented in the previous section could reflect only very short-lived price pressure or an immediate contrarian response to retail trading. To address this, we recompute cumulative stock returns starting from week $w+1$, excluding the first week after the order imbalance signal, and re-estimate equation (4). Graph B of Figure 1 shows that the coefficients on both order imbalance measures remain positive and continue to rise with the holding period. This pattern indicates that cumulative return predictability is not driven solely by the first week following the order imbalance signal.

Given Nokia's large weight in the Finnish equity market, a natural concern is that our results may be driven by a single dominant firm. In the Appendix, we show that all our main predictability results remain virtually unchanged when Nokia is excluded from the sample.

*** Appendix 1 ***

Taken together, the k-week ahead regressions and the cumulative return regressions suggest that short-term price pressure or short-lived contrarian trading alone cannot explain our results. Instead, retail order flow is associated with a sustained drift in stock returns over several weeks.

IV.D Economic Mechanisms Behind Long-Term Stock Return Predictability

Having established that retail order imbalance predicts both weekly and 15-week cumulative future stock returns, we next examine the underlying economic mechanisms. Prior work has proposed several distinct channels. Kaniel, Saar, and Titman (2008) emphasize that the contrarian nature of retail order flow allows individuals to implicitly provide liquidity to other market participants who demand immediacy, thereby forecasting subsequent returns.

Chordia and Subrahmanyam (2004) propose a price-pressure-based return predictability channel in which persistence in order flow induces temporary price pressure that subsequently reverts. Finally, Kelley and Tetlock (2013) and BJZZ argue that retail trading may reflect private information, consistent with an informed trading channel. The observed weekly return predictability of retail order flow in our data might be explained by some combination of liquidity provision, persistence of retail order flow, and informed trading. Cumulative return predictability, which extends over 15 weeks, is unlikely to be explained by liquidity provision or temporary price pressure, both of which imply short-lived return effects. The persistence of both weekly and cumulative return predictability is consistent with an information-based channel in which information embedded in retail order flow is gradually impounded into prices.

To assess whether this information channel operates through public information processing or through information orthogonal to observable public news, we follow the two-stage decomposition methodology proposed by BJZZ. This approach allows us to separate retail order imbalance into components associated with persistence, contrarian trading, public news sentiment, and a residual component orthogonal to these channels.

We obtain intraday structured summaries of material news and events from the Key Development Plus database. The database is offered by S&P Global and contains prominent news and events, grouped into categories, including earnings, dividends, mergers and acquisitions, buybacks, public offerings, management changes, debt defaults, dividend cancellations, and regulatory agency inquiries[3]. The database provides key information about each news/event item, such as ISIN, the date/timestamp of announcement, the news headline,

[3] Key Development Plus database provides news and events in 88 categories. Earnings related news account for 32% of news-timestamp observations. M&A, buyback, and executive/board changes are the next three largest categories.

and the news summary text. Since this data does not provide a ready-to-use sentiment measure of news, we construct a sentiment score using a large language model.

We employ a large language model(gpt5-nano) to quantify the sentiment of firm-level news abstracts. For each news item, the model assigns a continuous sentiment score bounded between −1 and 1, wherein higher values indicate favourable implications for the firm, lower values indicate adverse information, and zero corresponds to neutral or mixed news. The scoring is based solely on the textual content of the news abstract and reflects the model's assessment of the directional implications of the disclosed information. This approach allows us to transform qualitative disclosures into a standardized numerical measure suitable for large-scale empirical analysis. The news data spans January 2005 to December 2022. We use ISIN to match the sentiment data with our retail order imbalance data.

In the first stage of decomposition analysis, we decompose weekly order imbalance into four components. Specifically, each trading day, we estimate the following cross-sectional regression using weekly (5-day) variables:

$$oib_{i,w-1} = e0_{w-1} + e1_{w-1} oib_{i,w-2} + e2'_{w-1} Ret_{i,w-2} + e3_{w-1} \mathrm{sent}_{i,w-1} + u3_{i,w-1}$$

Following BJZZ, $\mathrm{sent}_{i,w-1}$ is the contemporaneous public news sentiment for firm *i* during week *w*-1, measured as the average non-missing news sentiment score for firm *i* during week *w*-1.

Next, using the time series of coefficients, we decompose $oib_{i,w-1}$ in to the following:

$$\widehat{persistence}_{i,w-1} = \mathrm{e}\widehat{1_{\mathrm{i,w-1}}}\mathrm{oib}_{\mathrm{i,w-2}}$$

$$\widehat{\mathrm{contrarian}}_{\mathrm{i,w-1}} = \mathrm{e}\widehat{2'_{\mathrm{i,w-1}}}\mathrm{Ret}_{\mathrm{i,w-2}}$$

$$\widehat{publicnews}_{i,w-1} = \mathrm{e}\widehat{3_{\mathrm{i,w-1}}}\mathrm{sent}_{\mathrm{i,w-1}}$$

$$\widehat{other_{i,w-1}} = \mathrm{e}\widehat{0_{\mathrm{i,w-1}}} + \mathrm{u}\widehat{3_{\mathrm{i,w-1}}}$$

In the second stage, we use the estimated persistence, contrarian, public-news, and other component to run the following predictive regression using the Fama-Macbeth (1973) procedure.

$$ret_{i,w:w+14} = \mathrm{f0}_w + \mathrm{f1}_w \widehat{\mathrm{persistence}}_{\mathrm{i,w-1}} + \mathrm{f2}_\mathrm{w} \widehat{\mathrm{contrarian}}_{\mathrm{i,w-1}} + \mathrm{f3}_\mathrm{w} \widehat{\mathrm{other}}_{\mathrm{i,w-1}} + \mathrm{f4}'_\mathrm{w} \mathrm{Ret}_{\mathrm{i,w-1}} + \mathrm{f5}_\mathrm{w} \widehat{publicnews}_{i,w-1} + \mathrm{u4}_{\mathrm{i},w+1:w+14}$$

The results are reported in Table 7. Panel A reports the first-stage estimation results. The positive and statistically significant coefficients on contemporaneous public news sentiment indicate that retail trading covaries with firm-specific news; retail investors tend to buy (sell) more of stocks that are associated with contemporaneous positive (negative) news surprises, respectively. Retail order flow is also persistent and contrarian with respect to past returns, consistent with our earlier results in Table 3. These patterns indicate that retail investors both respond to public news and exhibit sustained trading behaviours. Our results are similar to those found in BJZZ .

*** Table 7 ***

We report the second-stage decomposition results in Panel B of Table 7. For volume-based order imbalance reported in column (1), both the persistence and other components significantly predict future stock returns, whereas contrarian and public news components are statistically insignificant. The estimated coefficients are 0.0485 (t-stat = 2.25) for persistence, 0.0017 (t-stat =0.24) for contrarian trading, -0.0770 (t-stat=1.06) for public news, and 0.0069 (t-stat=7.21) for the other component.

The lack of predictive power for public-news component suggests that retail investors' contemporaneous trading around observable public news does not materially contribute to

long-horizon return predictability. [4]Instead, predictability is driven by persistence and other components. The other component captures variation in retail order flow that is orthogonal to public news and mechanical trading patterns, consistent with retail investors trading on information not captured by the measured public news releases. Economically, moving from the 25th to the 75th percentile of the other component is associated with a 0.88% increase in 15-week cumulative returns.

The persistence component exhibits the largest economic magnitude: an interquartile-range increase implies a 2.51% increase in 15-week cumulative returns. The joint importance of persistence and the other component suggests that retail investors' information advantage manifests partly through sustained directional trading patterns, consistent with gradual information incorporation rather than short-lived price pressure. Such persistence may reflect informed investors slowly building positions or updating trades as private signals evolve. The results are similar when using the trade-based order imbalance measure. Persistence and the other component continue to predict future stock returns, while the contrarian and public-news components remain statistically insignificant.

Taken together, the decomposition analysis indicates that the long-term predictive power of retail order flow is consistent with an information-based channel operating through sustained trading and information orthogonal to observable public news, rather than through transient liquidity provision or temporary price pressure.

V. Empirical Tests and Results of Heterogenous Retail Investors

The predictability results in the previous section treat retail investors as a homogenous group. Prior papers find that investor characteristics such as age, location, sophistication, and gender influence stock market participation, portfolio choice, and investment performance

[4] While our public news measure captures firm-specific structured disclosures, it may not fully reflect all publicly available information, leaving scope for information effects beyond measured news sentiment

(Campbell, 2006; Guiso and Sodini, 2013; Korniotis and Kumar, 2011; Gomes, Haliassos, and Ramadorai, 2021). This suggests that retail investors differ in information, trading motives, and constraints. If these differences are systematic, one might expect return predictability to vary across investor groups.

Before turning to specific dimensions of heterogeneity, we first examine whether our baseline predictability results are driven by a small subset of investors with potentially distinct information or expertise embedded in retail order flow. Our data allow us to identify the personal trades of company insiders and employees of financial institutions (brokers). Because insiders and brokers are relatively few and trade infrequently, their order flows are not suitable for testing return predictability on their own. Instead, we ask whether excluding their trades alters the predictive power of aggregate retail order imbalance. To test this, we estimate equation (4) by using retail order imbalances adjusted to exclude insiders' and brokers' trades. The results are reported in Table 8. The coefficients on the insider- and broker-adjusted order imbalance remain positive, statistically significant, and similar in magnitude to those reported in Table 6. This suggests that our main predictability results are not an artefact of insider/brokers' activity being misclassified as retail trading.

*** Table 8 ***

Having ruled out insiders and brokers as the main drivers of return predictability, we next examine heterogeneity in the predictive power of retail investors along four dimensions: geography, age, sophistication, and gender. All subsequent analyses exclude trades by insiders and brokers.

V.A Retail Order Imbalance of Local and Distant Investors and Return Predictability

We begin by examining whether the geographic distance between investors and firms matters for return predictability of retail investor trades. Prior works (Coval and Moskowitz,

2001; Ivković and Weisbenner, 2005) show that investors may exploit proximity to firms to generate valuable information. If proximity facilitates information acquisition, one might expect stronger return predictability for trades placed by local investors.

To test for heterogeneity by distance, we first compute the geographic distance between investors and firms by using postcode information from Euroclear (for investors) and Compustat Global (for firms). Because investors may trade firms in multiple locations, we classify individual trades, rather than investors, as local or distant. Specifically, we sort trades into terciles based on investor-firm distance. The mean (median) distance is 13 (10) kilometers for the closest tercile, 137 (145) kilometers for the middle tercile, and 385 (341) kilometers for the most distant tercile, respectively. Median trade size is identical across groups (200 shares), mitigating concerns that differences in predictability are driven by variation in order size.

We then construct separate weekly order imbalances for each distance tercile and jointly examine their ability to predict stock returns by estimating equation (4).

*** Table 9 ***

Column (1) of Table 9 reports the estimation results for volume-based order imbalance. The coefficient on the order imbalance of the closest group is 0.0036 (t-stat=5.65), indicating that the trading activity of local retail investors significantly predicts the cross-section of 15-week cumulative stock returns. By contrast, the coefficients on order imbalances of the two more distant groups are smaller in magnitude and statistically weaker. The predictive power of local investors is economically meaningful. Moving from the 25th percentile to the 75th percentile of local order imbalance results in a 15-week cumulative return difference of 0.714%, compared to 0.4289% and 0.3839% for the middle and most distant groups, respectively. Column (2) shows similar patterns when order imbalance is measured using the number of trades, with local order flow continuing to exhibit the strongest predictive power.

Taken together, these results indicate that the predictive power of retail order flow declines with investor–firm distance, consistent with geographic proximity facilitating access to information relevant for future stock returns.

V.B Retail Order Imbalance Across Investor Age Groups and Return Predictability

The second dimension of heterogeneity we examine is investor age. Prior work shows that age is associated with differences in risk-taking, trading behaviour, and portfolio adjustment, reflecting variation in experience, cognitive capacity, and market engagement (Korniotis and Kumar, 2011). These differences suggest that the information content of retail trades may vary systematically across age groups.

Our data report the date of birth of account holders, allowing us to compute investor age at the time of each trade. We group retail investors into five age categories based on the age of the account holder: 25 years or younger, 26–40, 41–55, 56–68, and older than 68. These groups account for 7%, 24%, 32%, 24%, and 13% % of the total number of trades, respectively. We construct order imbalances separately for each age group and examine whether the return predictability is concentrated in specific age cohorts.

We begin by estimating equation (4) separately for each age group where we include the order imbalance of one age group at a time along with our standard controls. The results are reported in Table 10, with Panel A for volume-based order imbalance and Panel B for trade-based order imbalance. Columns (1)-(5) in Panel A show that order imbalances for all age groups have positive and significant coefficients when considered in isolation. However, both the statistical significance and economic magnitude is the largest for the 26-40 group: moving from the 25th percentile to the 75th percentile of order imbalance for this group results in a 1.1% increase in 15-week cumulative return.

*** Table 10 ***

To distinguish which age cohorts matter once we control for trading of other cohorts, we then estimate a joint regression where we include order imbalance of all age groups simultaneously. Column (6) in Panel A reports the joint estimation and shows that the predictive power is concentrated among the first four categories, which together constitute the working age population in our sample. The 26-40 age group continues to exhibit the strongest predictive power. In contrast, the coefficient on the order imbalances of investors past retirement age shrinks substantially and is no longer significant in the joint estimation. The patterns in Panel B that reports estimation results for number of trades-based order imbalance are very similar. This pattern is generally consistent with findings that older investors trade less effectively (Korniotis and Kumar, 2011).

V.C Retail Order Imbalance of Sophisticated and Naive Investors and Return Predictability

The third dimension of heterogeneity we examine is investor sophistication. Prior literature finds that investor sophistication affects trading performance, with less sophisticated investors earning lower returns on average (Barber and Odean, 2000; Barber, Odean, and Lin 2023; Grinblatt and Keloharju, 2000; Campbell, Ramadorai, and Ranish, 2019; Eaton, Green, Roseman, and Wu, 2022). One would therefore expect that trades of financially sophisticated investors have stronger predictive power for the cross-section of stock returns.

Our data allows us to proxy for investor sophistication in two ways. The first proxy is based on the Euro value of investor account balances. Specifically, investors are classified into three groups based on their beginning-of-month account balance: investors in the top tercile (high account balance) are considered sophisticated, those in the bottom tercile are classified as naïve, and those in the middle tercile as intermediate, respectively. We construct separate order imbalances for the three groups and report the estimation results for equation (4) in Panel A of Table 11. Account balance data are available from Euroclear for the period September

2000 to January 2012; accordingly, the analysis using this proxy is restricted to this sample period.

Across Panel A, the coefficient on order imbalance decreases as we move from the high account balance group to lower account balance group. The coefficient on order imbalance for the high account balance group is in the range of 0.0051 and 0.0056 and exhibits a strong statistical significance. The low account balance group is statistically insignificant. In economic terms, moving from the 25th percentile to the 75th percentile of order imbalance for the high account balance group results in a 15-week cumulative return difference of 1.02%, compared to 0.444% and 0.285% for medium and lower balances, respectively. The same monotonic pattern holds when order imbalance is measured using the number of trades, as reported in column (2).

Our second proxy for sophistication is based on an investor's geographic location. We classify investors residing in the greater Helsinki area as sophisticated, reflecting the concentration of financial institutions and high-skilled occupations in Finland's financial center. We assume that investors not living the greater Helsinki area as naïve. We construct weekly order imbalances separately for the two groups and include both measures jointly in equation (4).

Panel B of Table 11 presents the results. Column (1), which reports estimation results for volume-based order imbalances shows that the coefficient on the order imbalance of sophisticated investors is 0.0052 (t-stat=8.5), whereas the coefficient on naïve order imbalance is substantially smaller at 0.0024 (t-stat=2.98). An interquartile range increase in weekly order imbalance of sophisticated investors is associated with an increase of 1% in 15-week cumulative return. The implied return spread for naïve investors is less than half of this size

(0.46%). This economic pattern holds for the predictability regression when order imbalance is measured using the number of trades, as reported in Column (2).

Taken together, both proxies for sophistication indicate that return predictability is concentrated in the trading activity of more sophisticated retail investors.

V.D Retail Order Imbalance of Male and Female Investors and Return Predictability

The fourth dimension of heterogeneity we examine is gender. Prior evidence documents that men trade more than women and that excessive trading hurts portfolio performance (Barber and Odean, 2001). Our setting allows us to ask a related but distinct question: whether the predictive power of retail order flow differs systematically by gender. Our data provide gender information associated with each account. In our sample, 79% of trades are from male investors and 21% from female investors. We compute order imbalances for male and female investors and jointly estimate equation (4) by including both male and female order imbalances.

The estimation results are reported in Table 12. Column (1) where we use volume-based order imbalance shows that coefficients on both male and female order imbalances are positive and statistically significant. However, the coefficient on female order imbalance (0.0017) is substantially smaller than the coefficient on male order imbalance (0.0053), both economically and statistically. Because men account for a larger fraction of total trading volume in our data and male and female order flows are highly correlated, male order flow dominates in joint specifications. Moving from the 25th percentile to the 75th percentile of order imbalance for male investors results in a 15-week cumulative return difference of 0.914%, compared to 0.384% for female investors. Similar results are obtained when we use number of trade-based order imbalance in column (2).

These results indicate that male investors' order flow has stronger predictive content for the cross-section of future returns. This finding is distinct from, and not inconsistent with,

prior evidence that men trade more frequently than women and that this overtrading reduces their own portfolio returns (Barber and Odean, 2001). Our results speak to the information content of trades for predicting relative performance across stocks, rather than the profitability of individual investors' portfolios.

VI. Stability of Results Over Time Periods

Our results in the previous sections are based on the full sample period of 1997 to 2022. There has been concern that the predictive power of retail order flow may have changed over time. Ardia, Aymard and Cenesizoglu (2024) find that retail predictability has weakened in the post-BJZZ period. Our data spans 26 years and thus allows us to evaluate the stability of results over time and to revisit these recent concerns. To examine the stability of our results across different time-periods, we re-estimate the baseline Fama–MacBeth regression in equation (4) separately for three subperiods: the pre-BJZZ period (1997–2009), the BJZZ sample period (2010–2015), and the post-BJZZ period (2016–2022).

The results are reported in Table 13. Across all three subperiods, the coefficient on retail order imbalance remains positive and statistically significant. In the pre-BJZZ period (1997–2009), the coefficients on volume-based order imbalance and trade-based order imbalance are 0.0064 (t-stat = 4.0) and 0.0080 (t-stat = 3.8), respectively, implying interquartile 15-week cumulative return differences of 1.17% and 1.32%, respectively. In the BJZZ period (2010–2015), the corresponding coefficients increase to 0.0081 (t-stat = 3.58) and 0.0071 (t-stat = 2.9), with interquartile 15-week cumulative return spreads of 0.93% and 0.79%. In the post-BJZZ period (2016–2022), the coefficients remain positive at 0.0068 (t-stat = 4.34) for volume-based order imbalance and 0.0078 (t-stat = 5.46) for trade-based order imbalance, associated with interquartile 15-week cumulative return differences of 1.07% and 1.21%. Thus, there is no evidence of a structural decline in the cross-sectional predictive power of retail order

imbalance; if anything, the trade-count-based measure delivers the largest spread in the most recent period[5].

*** Table 13 ***

Overall, these results show that our main finding that retail order flow predicts the cross-section of weekly and 15-week cumulative stock returns is not confined to a specific part of our sample period. Retail trading remains a robust and economically meaningful predictor of returns in the most recent years of our sample, alleviating concerns that the documented predictability is an artefact of a specific historical episode.

VII. Conclusion

In this paper, we use a complete dataset of all equity transactions by retail investors in Finland over 1997–2022 to study retail trading behaviour and its pricing implications. Unlike most existing work, our data do not suffer from mismeasurement problems that arise when retail trades or traders must be inferred from samples or trade-classification algorithms. We show that retail order imbalances predict the cross-section of stock returns over horizons up to several weeks, and that this predictability is consistent with a combination of persistent order flow and an information channel, rather than short-lived liquidity provision. The predictive power of retail order flow is stable across pre-BJZZ, BJZZ, and post-BJZZ subperiods, alleviating concerns that it is confined to a particular historical episode. Finally, by examining heterogeneity along four dimensions—geography, age, sophistication, and gender—we show that retail investors are not alike. The predictive power of retail order flow is higher among local investors, working-age investors, more sophisticated investors, as well as men. In contrast, return predictability is weaker or absent for distant, older, and less sophisticated

[5] In unreported results, we find the same pattern for the cross-section of weekly stock returns.

investors, suggesting substantial heterogeneity in how retail trading contributes to price discovery.

References

Ardia, David, Clement Aymard, and Tolga, Cenesizoglu, 2024, Revisiting Boehmer et al. (2021): Recent Period, Alternative Method, Different Conclusions, Working Paper.

Balasubramaniam, Vimal, John Y. Campbell, Tarun Ramadorai, and Benjamin Ranish, 2023, Who owns what? A factor model for direct stockholding, *Journal of Finance* 78, 1545–1591.

Barber, Brad M, Xing Huang, Philippe Jorion, Terrence Odean, and Christopher Schwarz, 2024, A (sub) penny for your thoughts: Tracking retail investor activity in TAQ. *Journal of Finance* 79 (4), 2403–2427.

Barber, Brad M., and Terrance Odean, 2000, Trading is hazardous to your wealth: The common stock investment performance of individual investors, *Journal of Finance* 55, 773−806.

Barber, Brad M., and Terrance Odean, 2001, Boys will be boys: Gender, overconfidence, and common stock investment, *Quarterly Journal of Economics* 116, 261–292.

Barber, Brad M., and Terrance Odean, 2008, All that glitters: The effect of attention and news on the buying behaviour of individual and institutional investors, *Review of Financial Studies* 21, 785–818.

Barber, Brad M., Terrance Odean, and Ning Zhu, 2009, Do retail trades move markets? *Review of Financial Studies* 22, 151−186.

Barber, Brad M., Lin Shengle, and Terrance Odean, 2023, Resolving a Paradox: Retail Trades Positively Predict Returns but Are Not Profitable. *Journal of Financial and Quantitative Analysis*, 1-35.

Barrot, Jean-Noel, Ron Kaniel, and David A. Sraer, 2016, Are retail traders compensated for providing liquidity? *Journal of Financial Economics* 120, 146–168.

Battalio, Robert, Robert Jennings, Megmet Salgam, and Jun Wu, 2024. Difficulties in obtaining a representative sample of retail trades from public data sources. Working Paper.

Betermier, Sebastien, Laurent E. Calvet, Samuli Knupfer, and Jense S Kvaerner, 2025, Investor factors, *Journal of Finance*, 1-41.

Boehmer, Ekkehart, Charles M. Jones, Xiaoyan Zhang, and Xinran Zhang, 2021, Tracking retail investor activity, *Journal of Finance* 76, 2249−2305.

Campbell, J. Y.; T. Ramadorai; and B. Ranish. “Do the Rich Get Richer in the Stock Market? Evidence from India.” *American Economic Review: Insights*, 1 (2019), 225–240.

Chordia, Tarun, and Avanidhar Subrahmanyam, 2004, Order imbalance and stock returns: Theory and evidence, *Journal of Financial Economics* 72, 485−518.

Coval, Joshua D., and Tobias J. Moskowitz, 1999, Home bias at home: Local equity preference in domestic portfolios, *Journal of Finance* 54, 145–166.

Dorn, Daniel, Gur Huberman, and Paul Sengmueller, 2008, Correlated trading and returns, *Journal of Finance* 58, 885–920.

Eaton, G. W.; T. C. Green; B. Roseman; and Y. Wu. “Retail Trader Sophistication and Stock Market Quality: Evidence from Brokerage Outages.” *Journal of Financial Economics*, 146 (2022), 502–528.

Fong, Kingsley Y.L, David R. Gallagher, and Adrian D. Lee, 2014, Individual investors and broker types, *Journal of Financial and Quantitative Analysis* 49, 431–451.

Gomes, Francisco, Michael Haliassos, and Tarun Ramadorai, 2021, Household finance, *Journal of Economic Literature* 59, 919–1000.

Gurrola Perez, Pedro, Lin, Kaitao and Speth, Bill, 2022, Retail Trading: An Analysis of Current Trends and Drivers, Working Paper.

Grinblatt, M., and M. Keloharju, 2000, The Investment Behaviour and Performance of Various Investor Types: A Study of Finland's Unique Data Set. *Journal of Financial Economics*, 55, 43–67.

Guiso, Luigi, and Paolo Sodini, 2013, Household finance: An emerging field, in George M. Constantinides, Milton Harris, and Rene M. Stulz, eds.: *Handbook of the Economics of Finance*, Volume 2 (North Holland, New York, NY).

Hvidkjaer, S., 2008. Small trades and the cross-section of stock returns. *Review of Financial Studies* 21, 1123–1151.

Ivković, Zoran, and Scott Weisbenner, 2005, Local does as local is: Information content of the geography of individual investors' common stock investments, *Journal of Finance* 60, 267–306.

Jones, Charles M, Donghui Shi, Xiaoyan Zhang, and Xinran Zhang, 2025, Retail trading and return predictability in China, *Journal of Financial and Quantitative Analysis* 60, 68-104.

Kaniel, Ron, Shuming Liu, Gideon Saar, and Sheridan Titman, 2012, Individual investor trading and return patterns around earnings announcements, *Journal of Finance* 67, 639–680.

Kaniel, Ron, Gideon Saar, and Sheridan Titman, 2008, Individual investor sentiment and stock returns, *Journal of Finance* 63, 273−310.

Kelley, Eric K and Paul C. Tetlock, 2013, How wise are crowds? Insights from retail orders and stock returns, *Journal of Finance* 68, 1229–1265.

Kogan, Shimon, Igor Makarov, Marina Niessner, and Antoinette Schoar, 2024. Are cryptos different? evidence from retail trading. *Journal of Financial Economics* 159, 103897.

Korniotis, George, and Alok Kumar, 2011, Do older investors make better investment decisions? *Review of Economics and Statistics* 93, 244–265.

Laarits, Thomas and Marco Sammon, 2025, The retail habitat, *Journal of Financial Economics*, 104144.

Linnainmaa, Juhani T., 2010, Do limit orders alter inferences about investor performance and behaviour? *The Journal of Finance*, 65(4), 1473-1506.

McLean, David, Jeffrey Pontiff, and Christopher Reilly, 2025, Taking sides on return predictability, *Journal of Financial Economics,* 104158

Newey, Whitney K and Kenneth D. West, 1987, A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix, *Econometrica* 55, 703−708.

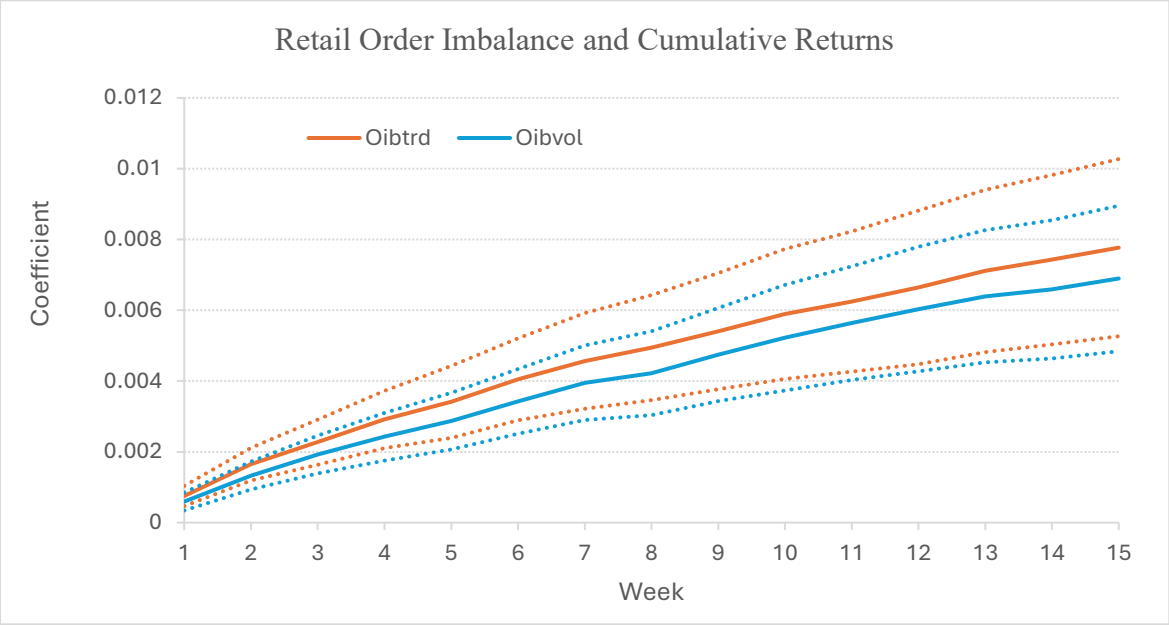
U.S. Government Accountability Office. (2005). Decimal Pricing Has Contributed to Lower Trading Costs and a More Challenging Trading Environment (GAO-05-3), GAO.

Welch, Ivo, 2022. The wisdom of the Robinhood crowd. *Journal of Finance* 77 (3), 1489–1527.

Figure 1: Retail Trading and Cumulative Stock Returns

The figure displays estimates of the coefficient on $oib_{i,w-1}$ in equation (4) where the dependent variable is cumulative stocks returns over k-weeks. Graph A shows coefficients when cumulative returns start from week *w* whereas Graph B shows coefficients where cumulative returns start from week *w+1*. Our sample period is January 1997 to December 2022 and our sample firms are common stocks from Finland. Dashed lines represent 95% confidence intervals.

Graph A: Cumulative returns over week *w* to *w+14*



Graph B: Cumulative returns over week *w+1* to *w+14*

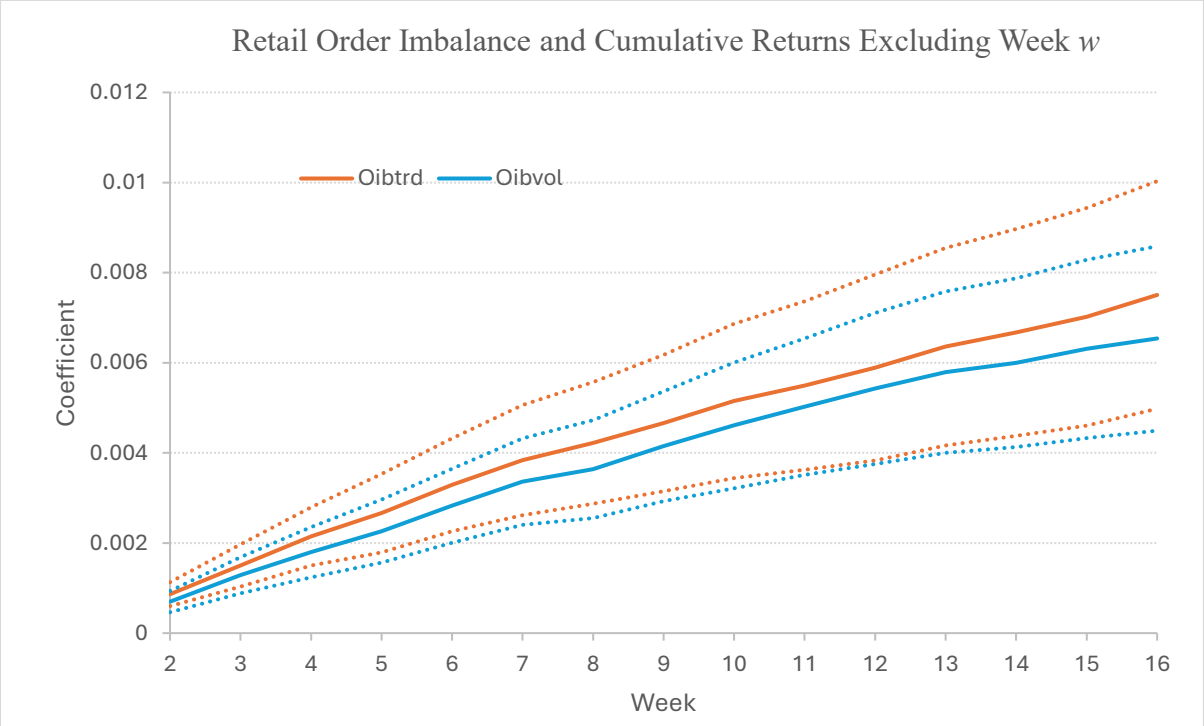


Table 1: Characteristics of Various Exchanges Across the World

The table reports the total traded value in 2022 for leading exchange groups in U.S. and Europe. These data are sourced from the World Federation of Exchanges; statistics accessed 20 Nov 2025.

Panel A: Total traded value

Year	Exchange	Currency	Value Traded (billions)
2022	NYSE	USD	24,060.39
2022	Nasdaq - US	USD	16,238.59
2022	Euronext	EUR	5,664.21
2022	LSE Group London Stock Exchange	GBP	2,557.28
2022	Deutsche Boerse AG	EUR	1,764.95
2022	Nasdaq Nordic and Baltics	EUR	1,734.19

Panel B: Average trade size in shares

	2002	2012	2022	Percent change 2002-2022
Finland (Nasdaq Helsinki)	4491	857	385	-91%
U.S. (Nasdaq-listed, all venues)[6]	735	249	149	-80%

[6] For the U.S., average trade size is computed for Nasdaq-listed (Tape C) securities aggregated across all trading venues. The 2002 U.S. value is taken from the U.S. Government Accountability Office (GAO) analysis of NYSE and Nasdaq trading data.

Table 2: Summary Statistics

This table reports summary statistics for our measure of retail investor trading activity. Our sample period is January 1997 to December 2022 and our sample firms are common stocks from Finland. Across all stocks and all days, we report the pooled sample mean for retail buy volume (*bvol*), retail sell volume (*svol*), retail buy trades (*btrd*), retail sell trades (*strd*). We construct two measures of retail order imbalance for each stock *i* on each date *t:*

$$oibvol_{i,t} = \frac{bvol_{i,t} - svol_{i,t}}{bvol_{i,t} + svol_{i,t}}$$

$$oibtrd_{i,t} = \frac{btrd_{i,t} - strd_{i,t}}{btrd_{i,t} + strd_{i,t}}$$

	count	mean	sd	p50	p25	p75
bvol	551648	45081.642	2116947.819	4925.000	1230.000	19161.000
svol	551648	42581.091	2718240.951	5090.000	1310.000	19428.000
btrd	551648	54.731	442.564	13.000	5.000	37.000
strd	551648	40.345	196.289	12.000	5.000	33.000
oibvol	551648	-0.010	0.437	0.000	-0.254	0.233
oibtrd	551648	0.044	0.378	0.000	-0.157	0.278

Table 3: Determinants of Retail Order Imbalances

This table reports determinants of retail investor trading activity. Our sample period is January 1997 to December 2022, and our sample firms are common stocks from Finland. We estimate the following Fama-MacBeth (1973) regression:

$$oib_{i,w} = b0_w + b1_w oib_{i,w-1} + b2'_w X_{i,w-1} + u1_{i,w} \quad (1)$$

where $oib_{i,w}$ is order imbalance for week *w.* The dependent variables are two scaled retail order imbalance measures: *oibvol* (based on the number of shares traded) and *oibtrd* (based on the number of trades). As independent variables, we include the previous-week return, *ret*(*w*−1), previous-month return, *ret*(*m*−1), and previous six-month return, *ret*(*m*−7, *m*−2). The control variables are log monthly turnover (*lmto*), monthly volatility of daily returns (*lvol*), log market cap (*size*), and log book-to-market ratio (*lbm*), all measured at the end of the previous month. To account for serial correlation in the coefficients, the standard errors of the time series are adjusted using Newey-West (1987), with optimal bandwidths chosen by following Newey and West (1994).

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	oibvol	oibvol	oibvol	oibtrd	oibtrd	oibtrd
oib(*w-1*)	0.4551***	0.4217***	0.4146***	0.5596***	0.5320***	0.5248***
	(107.28)	(99.95)	(99.40)	(148.50)	(136.00)	(135.95)
Ret(w−1)		-1.6820***	-1.7793***		-1.0667***	-1.1380***
		(-16.38)	(-16.56)		(-11.94)	(-12.28)
Ret(m−1)		-0.9047***	-0.9686***		-0.6316***	-0.6804***
		(-18.73)	(-19.00)		(-15.38)	(-15.87)
Ret(m−7,m−2)		-0.2693***	-0.2595***		-0.1851***	-0.2000***
		(-16.21)	(-14.97)		(-12.76)	(-13.16)
Lmto			0.0059*			0.0028
			(1.78)			(1.02)
Lvol			0.8741**			0.8075***
			(2.54)			(2.79)
Size			-0.0284***			-0.0078***
			(-9.69)			(-2.73)
Lbm			-0.0033			-0.0223***
			(-0.67)			(-5.26)
Intercept	-0.0335***	-0.0521***	0.1253***	0.0595***	0.0359***	0.0773***
	(-5.05)	(-7.01)	(4.80)	(7.54)	(4.27)	(3.56)
Adj. R^2	0.213	0.228	0.239	0.315	0.328	0.344

Table 4: Retail Order Flow and Short-Term Stock Returns

This table reports estimation results on whether retail investors' trading activity can predict the cross-section of one-week-ahead returns. Our sample period is January 1997 to December 2022 and our sample firms are common stocks from Finland. We estimate the following Fama-MacBeth (1973) regressions.

$$ret_{i,w} = d0_w + d1_w oib_{i,w-1} + d2'_w X_{i,w-1} + u2_{i,w} \quad (2)$$

The dependent variable is weekly individual stock returns. The independent variables are two scaled retail order imbalance measures: *oibvol* (based on the number of shares traded) and *oibtrd* (based on the number of trades). As independent variables, we include the previous-week return, *ret*(*w*−1), previous-month return, *ret*(*m*−1), and previous six-month return, *ret*(*m*−7, *m*−2). The control variables are log book-to-market ratio (*lbm*), log market cap (*size*), log monthly turnover (*lmto*), and monthly volatility of daily returns (*lvol*), all measured at the end of the previous month. To account for serial correlation in the coefficients, the standard errors of the estimated coefficients are adjusted using Newey-West (1987), with optimal bandwidths chosen by following Newey and West (1994).

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Return(w)	Return(w)	Return(w)	Return(w)	Return(w)	Return(w)
Order imbalance measure:	oibvol	oibvol	oibvol	oibtrd	oibtrd	oibtrd
oib(*w-1*)	0.0010***	0.0007***	0.0006***	0.0011***	0.0009***	0.0008***
	(7.01)	(5.15)	(4.63)	(7.41)	(5.63)	(5.18)
Ret(w−1)		-0.0587***	-0.0575***		-0.0579***	-0.0569***
		(-13.39)	(-13.56)		(-13.26)	(-13.41)
Ret(m−1)		0.0043*	0.0012		0.0050*	0.0018
		(1.66)	(0.48)		(1.89)	(0.72)
Ret(m−7,m−2)		0.0042***	0.0044***		0.0041***	0.0044***
		(3.80)	(4.25)		(3.76)	(4.27)
Lmto			0.0004***			0.0004***
			(3.27)			(3.19)
Lvol			-0.0412*			-0.0438**
			(-1.84)			(-1.96)
Size			-0.0003**			-0.0003**
			(-2.23)			(-2.37)
Lbm			0.0001			0.0002
			(0.43)			(0.67)
Intercept	0.0027***	0.0018***	0.0064***	0.0024***	0.0017***	0.0064***
	(3.88)	(2.78)	(4.88)	(3.56)	(2.59)	(4.91)
Adj. R^2	0.004	0.072	0.123	0.006	0.074	0.124
Interquartile weekly return diff	0.1517%	0.1099%	0.0937%	0.1752%	0.1333%	0.1148%

Table 5: Retail Order Flow and K-Week Ahead Stock Returns

This table reports estimation results on whether retail investor trading activity can predict the cross-section of stock returns k-weeks ahead. Our sample period is January 1997 to December 2022 and our sample firms are common stocks from Finland. We estimate Fama-MacBeth (1973) regressions, as specified in equation (3). Each row reports estimates from a separate regression. The dependent variable is the weekly individual stock return *k*-weeks ahead. The independent variables are two scaled retail order imbalance measures: *oibvol* (based on the number of shares traded) or *oibtrd* (based on the number of trades). To account for serial correlation in the coefficients, the standard errors of the estimated coefficients are adjusted using Newey-West (1987), with optimal bandwidths chosen by following Newey and West (1994). Control variables are the same as in Table 4 and are not reported.

	oibvol		oibtrd	
k weeks ahead	Coef.	*t*-stat	Coef.	*t*-stat
1 week	0.00060***	(4.63)	0.00075***	(5.18)
2 weeks	0.00070***	(5.82)	0.00086***	(6.39)
3 weeks	0.00059***	(5.17)	0.00066***	(4.86)
4 weeks	0.00052***	(4.29)	0.00065***	(4.89)
5 weeks	0.00046***	(3.87)	0.00053***	(3.11)
7 weeks	0.00050***	(4.20)	0.00050***	(3.68)
9 weeks	0.00047***	(3.83)	0.00039***	(2.78)
11 weeks	0.00043***	(3.69)	0.00038***	(2.82)
13 weeks	0.00034***	(2.84)	0.00042***	(3.04)
15 weeks	0.00038***	(3.11)	0.00042***	(3.13)

Table 6: Retail Order Flow and Cumulative Long-Term (15-week) Stock Returns

This table reports estimation results on whether retail investors' trading activity can predict the cross-section of 15-week cumulative stock returns. Our sample period is January 1997 to December 2022 and our sample firms are common stocks from Finland. We estimate Fama-MacBeth (1973) regressions as specified in equation (4). The independent variables are two scaled retail order imbalance measures: *oibvol* (based on the number of shares traded) and *oibtrd* (based on the number of trades). As independent variables, we include the previous-week return, *ret*(*w*−1), previous-month return, *ret*(*m*−1), and previous six-month return, *ret*(*m*−7, *m*−2). The control variables are log book-to-market ratio (*lbm*), log market cap (*size*), log monthly turnover (*lmto*), and monthly volatility of daily returns (*lvol*), all measured at the end of the previous month. To account for serial correlation in the coefficients, the standard errors of the estimated coefficients are adjusted using Newey-West (1987), with optimal bandwidths chosen by following Newey and West (1994).

	(1)	(2)	(3)	(4)
Dependent variable:	15-Week Cum. Return	15-Week Cum. Return	15-Week Cum. Return	15-Week Cum. Return
Order imbalance measure:	oibvol	oibvol	oibtrd	oibtrd
oib(*w-1*)	0.0073***	0.0069***	0.0081***	0.0078***
	(6.58)	(6.58)	(6.18)	(6.08)
Ret(w−1)	0.0537*	0.0483*	0.0586*	0.0535*
	(1.82)	(1.71)	(1.91)	(1.85)
Ret(m−1)	0.0885***	0.0969***	0.0931***	0.1008***
	(3.97)	(4.33)	(4.08)	(4.46)
Ret(m−7,m−2)	0.0701***	0.0622***	0.0702***	0.0627***
	(5.52)	(5.10)	(5.59)	(5.20)
Lmto		0.0032*		0.0032*
		(1.92)		(1.91)
Lvol		-0.5908***		-0.5997***
		(-2.77)		(-2.81)
Size		-0.0027		-0.0030*
		(-1.54)		(-1.69)
Lbm		-0.0009		-0.0005
		(-0.25)		(-0.14)
Intercept	0.0312***	0.0695***	0.0368***	0.0296***
	(2.99)	(3.82)	(3.29)	(2.85)
Adj. R^2	0.070	0.124	0.070	0.125
Interquartile 15-week cum return diff	1.1484%	1.0857%	1.2376%	1.1851%

Table 7: Predictability Decomposition of Cumulative Long-Term Stock Returns Using Public News

This table reports estimation results on a decomposition of the predictive power of retail order flow for the cross-section of 15-weeks cumulative stock returns. Our sample period is January 2005 to December 2022, and our sample firms are common stocks from Finland. We estimate the following two-stage Fama-MacBeth (1973) regressions.

First stage: In the first stage, we decompose order imbalance variable in equation (2) into four components. We estimate the following cross-sectional regression each week *w-1*.

$$oib_{i,w-1} = e0_{w-1} + e1_{w-1} oib_{i,w-2} + e2'_{w-1} Ret_{i,w-2} + e3_{w-1} \text{sent}_{i,w-1} + u3_{i,w-1}$$

Where $\text{sent}_{i,w-1}$ is the average sentiment score generated by a Large Language Model using the public news. Next, we decompose $oib_{i,w-1}$ as following:

$$\widehat{persistence}_{i,w-1} = \text{e}\widehat{1_{\text{i,w}-1}}\text{oib}_{\text{i,w}-2}$$

$$\widehat{\text{contrarian}}_{\text{i,w}-1} = \text{e}\widehat{2'_{\text{i,w}-1}}\text{Ret}_{\text{i,w}-2}$$

$$\widehat{publicnews}_{i,w-1} = \text{e}\widehat{3_{\text{i,w}-1}}\text{sent}_{\text{i,w}-1}$$

$$\widehat{other_{i,w-1}} = \text{e}\widehat{0_{\text{i,w}-1}} + \text{u}\widehat{3_{\text{i,w}-1}}$$

Second stage: In the second stage, we use the estimated persistence, contrarian, publicnews, and other to estimate the following predictive regression.

$$\text{ret}_{\text{i,w:w+14}} = \text{f0}_w + \text{f1}_w\widehat{\text{persistence}}_{\text{i,w}-1} + \text{f2}_\text{w}\widehat{\text{contrarian}}_{\text{i,w}-1} + \text{f3}_\text{w}\widehat{\text{other}_{\text{i,w}-1}} + \text{f4}'_\text{w}\text{Ret}_{\text{i,w}-1} + \text{f5}_\text{w}\widehat{publicnews}_{i,w-1} + \text{u4}_{\text{i,w}}$$

Panel A reports the first-stage estimation results, where the order imbalance measures are decomposed into four components as specified above. Panel B reports the second-stage decomposition of order imbalance's predictive power, as specified above. The scaled retail order imbalance measures are *oibvol* (based on the number of shares traded) and *oibtrd* (based on the number of trades). The variable *oib(w−1, persistence)* is estimated in the first stage using past order imbalance and reflects price pressure. The variable *oib(w−1, contrarian)* is estimated in the first stage using past returns over different horizons and is connected to the liquidity provision hypothesis. The variable *oib(w−1, sent)* is estimated in the first stage using sentiment variable measured in week *w*-1 and proxies for order imbalances that predicts returns associated with news releases. This variable is connected to the news based trading hypothesis. The residual part of the previous week's order imbalance from the first-stage estimation is denoted as "other," which can be attributed to private information about future returns on the part of these retail investors. As additional control variables, we include previous-week return, *ret*(*w*−1), previous-month return, *ret*(*m*−1), and previous six-month return, *ret*(*m*−7, *m*−2). The control variables are log book-to-market ratio (*lbm*), log market cap (*size*), log monthly turnover (*lmto*), and monthly volatility of daily returns (*lvol*), all measured at the end of the previous month. To account for serial correlation in the coefficients, the standard errors of the estimated coefficients are adjusted using Newey-West (1987), with optimal bandwidths chosen by following Newey and West (1994).

Panel A: First Stage of Projecting Order Imbalance on Persistence, Past Returns, and Public News

	(1)	(2)
Dependent variable:	oibvol(*w*-1)	oibtrd(*w*-1)
oib(*w-2*)	0.3909***	0.5129***
	(86.75)	(114.41)
Ret(w−2)	-1.6036***	-1.1168***
	(-13.52)	(-10.39)
Ret(m−1)	-0.8555***	-0.6406***

	(-17.20)	(-14.23)
Ret(m−7,m−2)	-0.2118***	-0.1554***
	(-11.85)	(-9.74)
Sent(w-1)	0.0417*	0.0806***
	(1.90)	(4.39)
Intercept	-0.0490***	0.0867***
	(-6.36)	(9.50)
Adj. R^2	0.192	0.303

Panel B: Second-Stage Decomposition of Order Imbalance's Predictive Power

Dependent variable:	(1) 15-Week Cum. Return	(2) 15-Week Cum. Return
Order imbalance measure:	oibvol	oibtrd
oib(*w*−1,persistence)	0.0485**	0.0175***
	(2.25)	(4.27)
oib(*w*−1,contrarian)	0.0017	-0.0032
	(0.24)	(-0.30)
oib(*w*−1,publicnews)	-0.0770	0.2423
	(-1.06)	(1.43)
oib(*w*−1,other)	0.0069***	0.0072***
	(7.21)	(6.88)
Ret(w−1)	0.0554**	0.0592**
	(2.09)	(2.18)
Ret(m−1)	0.1006***	0.1103***
	(4.86)	(5.25)
Ret(m−7,m−2)	0.0669***	0.0693***
	(5.14)	(5.38)
Lmto	0.0080***	0.0082***
	(3.62)	(3.60)
Lvol	-0.6584***	-0.6684***
	(-2.63)	(-2.65)
Size	-0.0063***	-0.0068***
	(-3.58)	(-3.72)
Lbm	-0.0050	-0.0047
	(-1.50)	(-1.41)
Intercept	0.1031***	0.1037***
	(4.62)	(4.55)
Adj. R^2	0.105	0.106
Interquartile 15-week return diff oib(*w*−1, persistence):	2.5123%	1.2605%
Interquartile 15-week return diff oib(*w*−1, contrarian**):**	0.1266%	0.0638%

Interquartile 15-week return diff oib($w-1$, other)	0.8840%	0.8288%

Table 8: Retail Order Flow and Cumulative Long-Term Stock Returns Adjusted for Insiders' and Brokers' Trades

This table reports estimation results on whether retail investors' trading activity can predict the cross-section of 15-week cumulative stock returns. Our sample period is January 1997 to December 2022 and our sample firms are common stocks from Finland. We estimate Fama-MacBeth (1973) regressions as specified in equation (4). The independent variables are two scaled retail order imbalance measures: *oibvol* (based on the number of shares traded) and *oibtrd* (based on the number of trades). Order imbalance for a stock-date is constructed by removing all insiders' and brokers' buys and sells from total buys and sells, that is, (Total buy volume – Brokers' buy volume) – (Total sell volume – Brokers' sell volume) divided by (Total buy volume – Brokers' buy volume) + (Total sell volume – Brokers' sell volume). Order imbalance based on the number of trades is constructed analogously. To account for serial correlation in the coefficients, the standard errors of the estimated coefficients are adjusted using Newey-West (1987), with optimal bandwidths chosen by following Newey and West (1994).

Dependent variable:	(1) 15-Week Cumulative Return	(2) 15-Week Cumulative Return
Order imbalance measure:	oibvol	oibtrd
oib(*w-1*)	0.0070***	0.0078***
	(6.63)	(6.13)
Ret(w−1)	0.0483*	0.0535*
	(1.71)	(1.85)
Ret(m−1)	0.0967***	0.1006***
	(4.31)	(4.44)
Ret(m−7,m−2)	0.0621***	0.0626***
	(5.10)	(5.19)
Lmto	0.0032*	0.0032*
	(1.91)	(1.91)
Lvol	-0.5872***	-0.5954***
	(-2.75)	(-2.79)
Size	-0.0027	-0.0029*
	(-1.53)	(-1.68)
Lbm	-0.0009	-0.0005
	(-0.25)	(-0.14)
Intercept	0.0694***	0.0695***
	(3.82)	(3.83)
Adj. R^2	0.124	0.125
Interquartile 15-weeks cumulative returns diff	1.0931%	1.1941%

Table 9: Predicting Cumulative Long-Term Stock Returns Using Retail Order Flow of Local v. Distant Investors

This table presents regression results examining whether the trading activity of local versus distant retail investors predicts the cross-section of 15-week cumulative stock returns. The sample consists of common stocks listed in Finland from January 1997 to December 2022. Trades of insiders and brokers are excluded from the sample. Investors are classified into three groups based on their geographic proximity to the firm. Specifically, trades are sorted in terciles based on the distance between the investor and the firm. Investors in group 1 are closest to the firm and investors in group 3 are the farthest. We estimate Fama-MacBeth (1973) regressions as specified in equation (4). Column (1) uses retail order imbalance based on the number of shares traded, measured over the previous week. Column (2) uses retail order imbalance based on the number of trades. To account for serial correlation in the coefficients, the standard errors of the estimated coefficients are adjusted using Newey-West (1987), with optimal bandwidths chosen by following Newey and West (1994).

Dependent variable:	(1) 15-Week Cumulative Returns	(2) 15-Week Cumulative Returns
Order imbalance	oibvol	oibtrd
oib1 (*w-1*)	0.0036***	0.0036***
	(5.65)	(4.95)
oib2 (*w-1*)	0.0020***	0.0020***
	(3.85)	(3.20)
oib3 (*w-1*)	0.0018***	0.0019**
	(2.89)	(2.56)
Ret(w−1)	0.0494*	0.0485*
	(1.86)	(1.80)
Ret(m−1)	0.0988***	0.0997***
	(4.39)	(4.42)
Ret(m−7,m−2)	0.0627***	0.0627***
	(5.05)	(5.10)
Lmto	0.0030*	0.0028*
	(1.81)	(1.68)
Lvol	-0.5704***	-0.5697***
	(-2.70)	(-2.71)
Size	-0.0022	-0.0025
	(-1.27)	(-1.42)
Lbm	-0.0006	0.0001
	(-0.15)	(0.01)
Intercept	0.0635***	0.0631***
	(3.49)	(3.46)
Adj. R^2	0.155	0.154
Interquartile 15-week cumulative return diff-Oib1	0.7138%	0.6709%
Interquartile 15-week cumulative return diff-Oib2	0.4289%	0.4028%
Interquartile 15-week cumulative return diff-Oib3	0.3839%	0.3723%

Table 10: Predicting Cumulative Long-Term Stock Returns Using Retail Order Flow by Investor Age Groups

This table reports estimation results on whether trading activity by retail investors of different age groups predicts the cross-section of 15-week cumulative stock returns. The sample includes all common stocks listed in Finland from January 1997 to December 2022. Trades executed by insiders and brokers are excluded. Retail investors are categorized into five age groups: (i) 25 years or younger, (ii) 26–40 years, (iii) 41–55 years, (iv) 56–68 years, and (v) older than 68. We construct two measures of order imbalance for each group: one based on the number of shares and the other based on the number of trades. All regressions follow the Fama-MacBeth (1973) approach as specified in Equation (4). Panel A reports estimation results for volume-based order imbalance whereas Panel B reports estimation results for trade-based order imbalance. Columns (1)–(5) include order imbalance for one age group at a time; Column (6) includes order imbalances for all age groups jointly. To account for serial correlation in the coefficients, the standard errors of the estimated coefficients are adjusted using Newey-West (1987), with optimal bandwidths chosen by following Newey and West (1994).

Panel A: Predicting Cumulative Long-Term Stock Returns Using Volume-Based Order Imbalance

	(1)	(2)	(3)	(4)	(5)	(6)
Order imbalance	oibvol	oibvol	oibvol	oibvol	oibvol	oibvol
oib 1 (*w-1*)	0.0030***					0.0014**
	(4.42)					(2.32)
oib 2 (*w-1*)		0.0051***				0.0039***
		(7.33)				(6.58)
oib 3 (*w-1*)			0.0037***			0.0021***
			(5.87)			(4.07)
oib 4 (*w-1*)				0.0030***		0.0015***
				(4.80)		(2.93)
oib 5 (*w-1*)					0.0015**	-0.0000
					(2.08)	(-0.05)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.122	0.123	0.122	0.122	0.122	0.127
Interquartile 15-week cumulative return difference	0.6732%	1.110%	0.8025%	0.6908%	0.3547%	

Panel B: Predicting Cumulative Long-Term Stock Returns Using Number of Trades-Based Order Imbalance

	(1)	(2)	(3)	(4)	(5)	(6)
Order imbalance	oibtrd	oibtrd	oibtrd	oibtrd	oibtrd	oibtrd
oib 1 (*w-1*)	0.0032***					0.0013**
	(4.37)					(2.02)
oib 2 (*w-1*)		0.0052***				0.0036***
		(6.34)				(5.30)

oib 3 (*w-1*)			0.0044***			0.0026***
			(5.95)			(4.65)
oib 4 (*w-1*)				0.0033***		0.0014**
				(4.50)		(2.32)
oib 5 (*w-1*)					0.0017**	-0.0002
					(2.07)	(-0.31)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.122	0.123	0.122	0.123	0.122	0.126
Interquartile 15-week cumulative return difference	0.6757%	1.0724%	0.9022%	0.7076%	0.3924%	

Table 11: Predicting Cumulative Long-Term Stock Returns Using Retail Order Flow of Sophisticated v. Naïve Investors

This table presents regression results examining whether the trading activity of sophisticated versus naïve retail investors predicts the cross-section of 15-week cumulative stock returns. Trades of insiders and brokers are excluded from the sample. We classify investors as sophisticated and naïve based on two proxies.

In Panel A, investors are classified in three groups based on their beginning of the month account balance. We estimate Fama-MacBeth (1973) regressions by including order imbalance of the three groups separately. Oib, High (*w-1*) is the order imbalance of investors with high account balance estimated over the past week. Oib, Low (*w-1*) is the order imbalance of investors with Low account balance estimated over the past week. The sample consists of common stocks listed in Finland from September 2000 to January 2012.

In Panel B, investors are classified as sophisticated if they are based in greater Helsinki region and naïve if they are living outside greater Helsinki area. We estimate Fama-MacBeth (1973) regressions by including order imbalance of sophisticated investors and naïve investors separately. The sample consists of common stocks listed in Finland from January 1997 to December 2022. To account for serial correlation in the coefficients, the standard errors of the estimated coefficients are adjusted using Newey-West (1987), with optimal bandwidths chosen by following Newey and West (1994).

Panel A: Account balance

Dependent variable:	(1) 15-Week Cum. Return	(2) 15-Week Cum. Return
Order imbalance	Oibvol	Oibtrd
Oib, High (*w-1*)	0.0051***	0.0056***
	(5.60)	(5.67)
Oib, Med (*w-1*)	0.0022**	0.0029**
	(2.06)	(2.44)
Oib, Low(*w-1*)	0.0012	0.0016
	(1.16)	(1.40)
Ret(w−1)	0.0410	0.0526
	(1.13)	(1.43)
Ret(m−1)	0.0938***	0.0993***
	(2.80)	(2.97)
Ret(m−7,m−2)	0.0532***	0.0544***
	(2.79)	(2.89)
Lmto	0.0032	0.0031
	(1.30)	(1.32)
Lvol	-1.0730***	-1.0649***
	(-3.54)	(-3.52)
Size	-0.0049**	-0.0052**
	(-2.22)	(-2.31)
Lbm	0.0056	0.0058
	(1.05)	(1.07)
Intercept	0.0868***	0.0880***
	(3.62)	(3.66)
Adj. R^2	0.144	0.144
Interquartile 15-week cumulative return diff-High	1.0217%	1.0671%

Interquartile 15-week cumulative return diff-Med	0.4448%	0.5786%
Interquartile 15-week cumulative return diff-Low	0.2851%	0.3534%

Panel B: Helsinki vs others

Dependent variable:	(1) 15-Week Cum. Return	(2) 15-Week Cum. Return
Order imbalance	Oibvol	Oibtrd
Oib Helsinki (*w-1*)	0.0052***	0.0058***
	(8.50)	(7.57)
Oib Other (*w-1*)	0.0024***	0.0023**
	(2.98)	(2.46)
Ret(w−1)	0.0502*	0.0534*
	(1.75)	(1.81)
Ret(m−1)	0.0989***	0.1004***
	(4.38)	(4.41)
Ret(m−7,m−2)	0.0623***	0.0627***
	(5.14)	(5.24)
Lmto	0.0033**	0.0032**
	(1.98)	(1.96)
Lvol	-0.5877***	-0.5836***
	(-2.75)	(-2.74)
Size	-0.0027	-0.0030*
	(-1.55)	(-1.72)
Lbm	-0.0010	-0.0007
	(-0.28)	(-0.18)
Intercept	0.0693***	0.0695***
	(3.81)	(3.84)
Adj. R^2	0.125	0.125
Interquartile 15-week cumulative return diff-Helsinki	1.0070%	1.0646%
Interquartile 15-week cumulative return diff-Other	0.4600%	0.4240%

Table 12: Predicting Cumulative Long-Term Stock Returns Using Retail Order Flow of Male v. Female Investors

This table reports estimation results on whether trading activity by retail investors of different genders predicts the cross-section of 15-weeks cumulative stock returns. The sample includes common stocks listed in Finland from January 1997 to December 2022. Trades executed by insiders and brokers are excluded from the analysis. We construct two measures of order imbalance for male and female investors: one based on the number of shares and the other based on the number of trades. All regressions follow the Fama-MacBeth (1973) approach as specified in Equation (4). To account for serial correlation in the coefficients, the standard errors of the estimated coefficients are adjusted using Newey-West (1987), with optimal bandwidths chosen by following Newey and West (1994).

Dependent variable:	(1) 15-Week Cumulative Returns	(2) 15-Week Cumulative Returns
Order imbalance measure:	Oibvol	Oibtrd
Oib Female (*w-1*)	0.0017***	0.0015**
	(2.69)	(2.02)
Oib Male (*w-1)*	0.0053***	0.0060***
	(6.76)	(6.52)
Ret(w−1)	0.0472*	0.0505*
	(1.66)	(1.73)
Ret(m−1)	0.0971***	0.1003***
	(4.28)	(4.37)
Ret(m−7,m−2)	0.0623***	0.0628***
	(5.15)	(5.25)
Lmto	0.0032*	0.0032*
	(1.96)	(1.93)
Lvol	-0.5652***	-0.5789***
	(-2.65)	(-2.71)
Size	-0.0026	-0.0030*
	(-1.50)	(-1.72)
Lbm	-0.0009	-0.0006
	(-0.23)	(-0.16)
Intercept	0.0685***	0.0696***
	(3.76)	(3.83)
Adj. R^2	0.125	0.125
Interquartile 15-weeks cumulative returns diff - Female	0.3848%	0.3439%
Interquartile 15-weeks cumulative returns diff - Male	0.9141%	0.9678%

Table 13: Retail Order Flow and Cumulative Long-Term Stock Returns Over Different Sample Periods

This table reports estimation results on whether retail investors' trading activity can predict the cross-section of 15-week cumulative stock returns. Our sample period is January 1997 to December 2022 and our sample firms are common stocks from Finland. We estimate Fama-MacBeth (1973) regressions as specified in equation (4) for three periods: pre-BJZZ period (1997-2009), BJZZ period (2010-2015), and post-BJZZ period (2016-2022). The independent variables are two scaled retail order imbalance measures: *oibvol* (based on the number of shares traded) and *oibtrd* (based on the number of trades). As independent variables, we include the previous-week return, *ret*(*w*−1), previous-month return, *ret*(*m*−1), and previous six-month return, *ret*(*m*−7, *m*−2). The control variables are log book-to-market ratio (*lbm*), log market cap (*size*), log monthly turnover (*lmto*), and monthly volatility of daily returns (*lvol*), all measured at the end of the previous month. To account for serial correlation in the coefficients, the standard errors of the estimated coefficients are adjusted using Newey-West (1987), with optimal bandwidths chosen by following Newey and West (1994).

Sample Period	Pre-BJZZ 1997-2009		BJZZ 2010-2015		Post-BJZZ 2016-2022	
Order imbalance	(1) Oibvol	(2) Oibtrd	(3) Oibvol	(4) Oibtrd	(5) Oibvol	(6) Oibtrd
oib(*w-1*)	0.0064***	0.0080***	0.0081***	0.0071***	0.0068***	0.0078***
	(4.01)	(3.75)	(3.58)	(2.90)	(4.34)	(5.46)
Ret(w−1)	0.0525	0.0603	0.0913**	0.0918**	0.0037	0.0082
	(1.07)	(1.20)	(2.15)	(2.10)	(0.10)	(0.23)
Ret(m−1)	0.1112***	0.1162***	0.1222***	0.1240***	0.0489*	0.0524*
	(2.93)	(3.02)	(3.44)	(3.46)	(1.67)	(1.80)
Ret(m−7,m−2)	0.0536***	0.0543***	0.0659***	0.0669***	0.0748***	0.0747***
	(2.70)	(2.77)	(3.37)	(3.44)	(3.90)	(3.90)
Lmto	0.0001	0.0001	0.0096***	0.0095***	0.0033	0.0034
	(0.04)	(0.04)	(3.11)	(3.09)	(1.33)	(1.34)
Lvol	-0.7255**	-0.7304**	-0.7294*	-0.7359	-0.2230	-0.2413
	(-2.27)	(-2.30)	(-1.65)	(-1.64)	(-0.64)	(-0.69)
Size	0.0004	0.0001	-0.0076***	-0.0079***	-0.0041*	-0.0043*
	(0.13)	(0.02)	(-2.92)	(-2.99)	(-1.65)	(-1.71)
Lbm	0.0037	0.0042	-0.0073	-0.0071	-0.0041	-0.0036
	(0.57)	(0.65)	(-1.30)	(-1.26)	(-0.83)	(-0.73)
Intercept	0.0436	0.0452	0.1217***	0.1216***	0.0729**	0.0707**
	(1.58)	(1.64)	(4.06)	(4.09)	(2.23)	(2.14)
Adj R^2	0.151	0.153	0.114	0.114	0.082	0.081
Interquartile 15-week cumulative returns diff	1.1711%	1.3221%	0.9377%	0.7969%	1.0709%	1.2188%

APPENDIX

Table IA.1: Retail Order Flow and Short-Term Stock Returns Excluding Nokia

This table reports estimation results on whether retail investors' trading activity can predict the cross-section of one-week-ahead returns. Our sample period is January 1997 to December 2022 and our sample consists of common stocks listed in Finland, excluding Nokia. We estimate the following Fama-MacBeth (1973) regressions.

$$ret_{i,w} = d0_w + d1_w oib_{i,w-1} + d2'_w X_{i,w-1} + u2_{i,w} \quad (2)$$

The dependent variable is weekly individual stock returns. The independent variables are two scaled retail order imbalance measures: *oibvol* (based on the number of shares traded) and *oibtrd* (based on the number of trades). As independent variables, we include the previous-week return, *ret*(*w*−1), previous-month return, *ret*(*m*−1), and previous six-month return, *ret*(*m*−7, *m*−2). The control variables are log book-to-market ratio (*lbm*), log market cap (*size*), log monthly turnover (*lmto*), and monthly volatility of daily returns (*lvol*), all measured at the end of the previous month. To account for serial correlation in the coefficients, the standard errors of the estimated coefficients are adjusted using Newey-West (1987), with optimal bandwidths chosen by following Newey and West (1994).

	(1)	(2)
Dependent variable:	Return(w)	Return(w)
Order imbalance measure:	oibvol	oibtrd
oib(*w-1*)	0.0006***	0.0007***
	(4.66)	(5.07)
Ret(w−1)	-0.0587***	-0.0581***
	(-13.69)	(-13.55)
Ret(m−1)	0.0011	0.0017
	(0.45)	(0.66)
Ret(m−7,m−2)	0.0046***	0.0046***
	(4.44)	(4.42)
Lmto	0.0004***	0.0004***
	(3.15)	(3.05)
Lvol	-0.0438**	-0.0462**
	(-1.97)	(-2.08)
Size	-0.0004***	-0.0004***
	(-2.69)	(-2.82)
Lbm	0.0001	0.0002
	(0.42)	(0.65)
Intercept	0.0069***	0.0068***
	(5.13)	(5.12)
Adj. R^2	0.124	0.125

Table IA.2: Retail Order Flow and Cumulative Long-Term (15-week) Stock Returns Excluding Nokia

This table reports estimation results on whether retail investors' trading activity can predict the cross-section of 15-week cumulative stock returns. Our sample period is January 1997 to December 2022 and our sample consists of common stocks listed in Finland, excluding Nokia. We estimate Fama-MacBeth (1973) regressions as specified in equation (4). The independent variables are two scaled retail order imbalance measures: *oibvol* (based on the number of shares traded) and *oibtrd* (based on the number of trades). As independent variables, we include the previous-week return, *ret*(*w*−1), previous-month return, *ret*(*m*−1), and previous six-month return, *ret*(*m*−7, *m*−2). The control variables are log book-to-market ratio (*lbm*), log market cap (*size*), log monthly turnover (*lmto*), and monthly volatility of daily returns (*lvol*), all measured at the end of the previous month. To account for serial correlation in the coefficients, the standard errors of the estimated coefficients are adjusted using Newey-West (1987), with optimal bandwidths chosen by following Newey and West (1994).

	(1)	(2)
Dependent variable:	15-Week Cum. Return	15-Week Cum Return.
Order imbalance measure:	oibvol	oibtrd
oib(*w-1*)	0.0068***	0.0075***
	(6.49)	(5.85)
Ret(w−1)	0.0450	0.0491*
	(1.63)	(1.73)
Ret(m−1)	0.0976***	0.1005***
	(4.40)	(4.48)
Ret(m−7,m−2)	0.0630***	0.0634***
	(4.90)	(4.94)
Lmto	0.0029*	0.0029*
	(1.74)	(1.73)
Lvol	-0.6542***	-0.6607***
	(-3.05)	(-3.08)
Size	-0.0038**	-0.0041**
	(-2.23)	(-2.40)
Lbm	-0.0013	-0.0009
	(-0.33)	(-0.23)
Intercept	0.0757***	0.0758***
	(4.21)	(4.21)
Adj. R^2	0.124	0.125

IA.1 Nasdaq Helsinki

Nasdaq Helsinki is part of the Nasdaq Nordic and Baltics exchange group, an integrated network of equity exchanges operating across Northern Europe and the Baltic region. During the sample period, the group comprises exchanges in Denmark (Nasdaq Copenhagen), Finland (Nasdaq Helsinki), Iceland (Nasdaq Iceland), Sweden (Nasdaq Stockholm), Estonia (Nasdaq Tallinn), Latvia (Nasdaq Riga), and Lithuania (Nasdaq Vilnius). While these exchanges share a common trading infrastructure and regulatory framework, the empirical analysis in this paper focuses exclusively on companies domiciled in Finland and listed on Nasdaq Helsinki.

Trading in Finnish equities listed on Nasdaq Helsinki is conducted electronically through a centralized limit order book. There are no designated liquidity providers, although firms may occasionally appoint a market maker to support liquidity. The market operates with an opening auction at 10:00 and closes at 18:30 (GMT), followed by a post-trading period that ends with a randomized closing auction. Since 2006, the Nasdaq Helsinki limit order book has been pre-trade anonymous.

All trades in Finnish stocks listed on Nasdaq Helsinki are subject to centralized reporting requirements. Exchange member broker-dealers must report executed trades through electronic routing to the central shareholder depository administered by Euroclear Finland Ltd. This reporting framework ensures comprehensive post-trade transparency for transactions involving Finnish-listed equities.

Off-market crossings are reported immediately for smaller trades, while larger block trades may be reported with a delay in accordance with regulatory rules. Reported transactions include trades executed on the Nasdaq Helsinki order book as well as trades in Finnish-listed equities executed on other trading platforms or through broker internalization mechanisms, aggregated at the security level.

Tick sizes on Nasdaq Helsinki vary by price level and liquidity classification. For liquid stocks with prices of euro 5 or more, the minimum tick size during the sample period is euro 0.001[7]. Tick size regimes are set by the exchange and are consistent with European market design standards.

Gurrola-Pérez et al. (2022) report that the share of retail investors' wealth held in equity securities is relatively high in the Nordic countries, with Finland at just under 40%. This share is similar in the U.S. Another way to measure the impact of retail investors is the participation in the share of order flow/dollar volume, which has recently risen to more than 35% in the U.S. (JP Morgan, 2025)[8]. The Nordic markets, including Finland, have not yet reached such high proportions of retail trading, and Finland's share of the traded value is approximately 5-7% of the total market.

[7] The tick sizes for stocks listed in Finland are determined by the European harmonized MiFID II tick size regime, so that the minimum tick size for stocks vary by the share's price level, and its average daily number of trades (liquidity band).

[8] https://am.jpmorgan.com/us/en/asset-management/liq/insights/market-insights/market-updates/on-the-minds-of-investors/who-is-buying-us-equities/