Retail Investors and Stock Return Predictability

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

First draft: December 2025
This draft: February 2026

Abstract

This study examines whether retail trading can predict short-term and long-term stock returns. Unlike prior research that relies on brokerage accounts or retail trade classification algorithms, we use a unique database of the entire universe of daily retail trades in Finland that has the following significant advantages: (i) It captures the complete market of all retail equity trades; (ii) covers a long period, spanning 26 years (1997-2022); (iii) retail investors are explicitly identified by the clearinghouse; (iv) whether the trade is a buy or sell order is explicitly identified by the clearinghouse; and (v) has data on investor characteristics that helps us examine the differing predictive abilities of heterogeneous types of retail investors. We find the following results: (i) The *aggregate* retail order imbalance predicts positive stock returns over the long-term (up to 15 weeks), and a long-short portfolio of retail order flow earns significant positive returns and alphas; (ii) retail investors tend to trade contrarian to past returns; (iii) the predictive content of retail investors' trades arises mainly from persistent order flow and private information not captured by observable public news; and (iv) Exploiting *investor heterogeneity,* we find that long-term 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 for distant, older, less-sophisticated investors, and females.

---

[a] Rutgers Business School, and [b] University of Sydney Business School, respectively. We thank Azi Ben-Raphael, Markus Brunnermeier, James Choi, Tony Cookson, Lauren Cohen, Daniel Dorn, Kingsley Fong, Clifton Green, David Hirshleifer, Toomas Larits, Sophia Li, Terry Odean, Lin Peng, Tavy Ronen, Mehrdad Samadi, Marc Sammon, Sheridan Titman, Stijn Van Nieuwerburgh, seminar participants at Rutgers and especially John Campbell for helpful comments and discussions. All errors remain our responsibility. Corresponding author: Darius Palia, dpalia@business.rutgers.edu

"… while useful insights can be derived from administrative data provided by financial services firms, *selection bias can limit the generalizability of inferences drawn from such data*. These datasets only tell us about the clients of the institution that is providing the data, and there is a risk that these clients are not representative of the whole population (emphasis added)."

Campbell and Ramadorai, 2025, p. 9

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 finds mixed evidence on whether retail traders can predict stock returns and thereby earn excess 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 (Kaniel, et. al, 2012; Kelley and Tetlock, 2013; Barber, Odean, and Zhu, 2008; Campbell, Ramadorai, and Schwartz, 2009; Boehmer, et. al, 2021; Farrell, et. al, 2022; Fedyk, 2023; Luo et. al, 2025; and McLean, Pontiff and Reilly, 2025). If retail investors have better information about a stock or the market portfolio, we would expect them to be contrarian traders investing in stocks that have gone down recently and when the overall market has gone down. Additionally, to minimize price impact and conceal private information of their informed trading, we would expect informed investors to order split their trades resulting in persistence in retail order flow over time. According to the informed retail trader hypothesis, a retail order imbalance would suggest a positive relationship with both short-term and long-term return predictability.[2] We

[1] See Section 2 of this paper for a more comprehensive and detailed explanation of the retail trading literature.
[2] There is considerable variation among various papers as to how one defines short-term and long-term returns. For consistent interpretation across papers, we define short-term as one month (four weeks), and greater than one month as long-term, respectively.

would also expect better informed retail investors to earn higher excess returns at both the short-term and long-term horizons.

The second strand of literature suggests that retail investors provide liquidity to institutional investors. Buy order balances are autocorrelated as retail investors repeatedly accommodate institutional order splitting. In turn, risk averse market makers raise prices for liquidity reasons, which results in a positive relationship between retail buy order imbalances and short-term return predictability and excess returns. This relationship turns to zero or negative in the long-term (Chordia and Subrahmanyam, 2004; Andrade, Chang and Seasholes, 2008; Dorn, Huberman, and Sengmuller, 2008; Kaniel, Saar, and Titman, 2008; Kaniel, et. al, 2012; and Barrot, Kaniel, and Sraer, 2016). Given that trading demand under the liquidity hypothesis is driven by institutional investors, one would not expect any (zero) relationship with the prior performance of individual stocks or the market portfolio.

The third strand of literature suggests that retail traders are noise traders with many behavioural biases such as overconfidence, return chasing, and the tendency to sell winners too quickly and hold on to losers too long (the disposition effect). Given a noise trader's behavioural biases, we would expect them to buy stocks that have done well (momentum stocks), and/or when the market has done well. These behavioural biases give rise to gradual trading and persistence in retail order flow over time. The trading philosophy of noise traders would suggest limited return predictability at both the short-term and long-term horizons -- which translates to zero or negative short- and long-term excess returns (Odean, 1998; Grinblatt and Keloharju, 2000; Swan and Westerholm, 2006; Barber and Odean, 2000, 2008; Seasholes and Wu, 2007; Hvidkjaer, 2008; Barber, Odean and Zhu, 2008; Linnainmaa, 2010; Fong, Gallagher and Lee, 2014; and Della Vedova, Grant and Westerholm, 2023). The expected relationships under the three different hypotheses are summarized in Table 1.

*** Table 1 ***

In an influential paper,[3] 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 Reporting Facilities (TRF). 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 Barber et al. (2024), Battalio 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, the empirical evidence has generally come from proprietary or small datasets (brokerage-level data covering narrow investor segments), or algorithmic classifications of identifying retail traders and signing the direction of their trades — which makes it difficult to draw broad conclusions about the impact of retail investors in price discovery (see the quote from Campbell and Ramadorai at the beginning of the paper).

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

[3] 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.

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) Can *aggregate* retail investor trading predict stock returns? Additionally, is this return predictability only over the short-term, or is it more long-term?

2) Does the aggregate retail investor's ability to predict stock returns translate to a high- v. low-retail order imbalance portfolio earning significant positive mean returns and alphas[4]?

3) If we find retail investors can predict stock returns over the long-term, we then examine the reasons behind their ability to predict — liquidity provision, better ability to interpret public information, or private information.

4) We examine whether the above relationships stay constant over time or vary across periods.

[4] Because we test return predictability using Fama–MacBeth cross-sectional regressions, the corresponding long–short trading strategy implied by these tests assigns equal weight to individual stocks. Accordingly, mean returns and alphas are evaluated using equal-weighted portfolios, consistent with the empirical specification. Our main results remain unchanged if we implement value-weighting or the modified equal-weighting schemes suggested by Barber, Lin, and Odean (2023).

5) Finally, we examine if there is substantial *heterogeneity* in retail traders' ability to predict long-term stock returns. Differential heterogeneity is measured for the following categories: local and distant retail investors, retail investors of different age groups, sophisticated and naive retail investors, and male and female retail investors, respectively.

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 individual stock and market returns is consistent with the informed retail trader. 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. Figure 1 illustrates this pattern by showing that the estimated return predictability increases with the holding horizon and exhibits no evidence of reversal. Importantly, the pattern remains when returns in the first week following the order imbalance signal are excluded, suggesting that the predictability is not driven by short-lived price pressure. 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 hypothesis, and against the liquidity and noise trader hypotheses. Our informed retail trader results are consistent with those found in Kaniel, et. al (2012), Kelley and Tetlock (2013), Barber, Odean, and Zhu (2008), Campbell, Ramadorai, and Schwartz (2009), BJZZ (2021), Farrell et. al (2022), Fedyk (2023), Luo et. al (2025), and McLean, Pontiff and Reilly (2025).

We answer the second question by constructing a long-short portfolio where we buy the stocks in the highest tercile of retail order imbalances, and short the stocks in the lowest tercile of retail order imbalances. We find that the long–short portfolio on the number of trades-based

retail order imbalances earns a buy-and-hold return of 1.115% over a 15-week holding horizon, with a corresponding alpha of 1.230% from the Fama-French four-factor model. These results indicate that the information content of retail trading can be exploited in a profitable trading strategy and that return predictability associated with retail traders is persistent over long horizons.

We then attempt to answer the third question above, wherein we examine which combination of liquidity provision, contrarian trading, better ability to interpret public information, or private information is driving their ability to predict long-term stock returns. 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. The BJZZ methodology separates retail order imbalance into various components associated with liquidity provision, contrarian trading, public news sentiment, and a residual component orthogonal to these forces (private information). We obtain intraday structured summaries of material news and events from the S&P Global's Key Development Plus database. This database 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. We construct a sentiment score using a large language model (GPT5-nano) to quantify the

sentiment of firm-level news abstracts. 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, the ability of informed retail investors to predict long-term stock returns is driven by persistence in order flow and private information t, while contrarian and public-news-based trading contribute little. These results are strongly consistent with those found in BJZZ.

To answer question four above, 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.

To address question five above, we examine whether our results are different for different types of informed 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 literature in household finance finds shows that demographic and economic characteristics such as age, wealth, sophistication or skill, and location shape participation, portfolio choice, and investment performance (Campbell, 2006; Guiso and

Sodini, 2013; Bach, Calvet, and Sodini, 2020; Coval et al, 2021; Gomes, Haliassos, and Ramadorai, 2021; Giglio et. al, 2021; Balasubramaniam et. al, 2023; Betermier et. al, 2025; and Campbell and Ramadorai, 2025). Our data allow us to extend their insight by examining the heterogeneous impact of order imbalances on stock return predictability along four key retail investor dimensions—location, age, sophistication, and gender, respectively.

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 of a lower economic magnitude. A one-interquartile range increase in local order imbalance is associated with a 0.71% increase in 15-week cumulative returns. These results are consistent with those found by Coval and Moskowitz (2001), Ivković and Weisbenner (2005), Massa and Simonov (2006), and Bernile, et. al (2015, 2019).

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 higher among working-age investors. Specifically, buy 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 retail 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 consistent with findings of Korniotis and Kumar (2011) that older investors trade less effectively.

The third dimension of heterogeneity we examine is investor 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 centre. 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 higher for Helsinki-based investors when compared to non-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 (79%) 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 retail order imbalance is associated with a 0.91% increase in 15-week cumulative stock returns, compared to 0.38% for female order imbalance. We find evidence consistent with those found in Wu and Westerholm (2014).

In sum, our results suggest that the average retail trader is an informed trader (using private information) who makes contrarian trades and whose order flows shows persistence. The extant literature had made the implicit assumption that all retail traders are equivalent to noise traders, or a subset of retail traders are informed. We find that "good" traders (local, sophisticated, working-age, male) possess a *higher magnitude of return predictability* than so-

called “bad” traders (distant, unsophisticated, older, female), but our “bad” traders also have predictive power.

A natural question is whether evidence from Finland generalizes to larger markets such as the U.S. While Finland is smaller in scale, our objective is not to extrapolate return magnitudes, but to examine whether retail order flow contains information that is incorporated gradually into prices when retail trades are observed without selection or classification error. In this respect, the Finnish equity market shares key structural features with major markets, including electronic trading with continuous price formation through exchange-based limit order books, alongside substantial institutional participation. Importantly, our measures of retail order imbalance are conceptually comparable[5] to those used in prior U.S. studies, such as BJZZ, but are constructed from directly observed retail trades rather than algorithmic inference. Moreover, Finnish equity data have been used extensively in the literature, including six published papers in the top-finance journals, reflecting its role as a laboratory for studying investor behaviour and price formation.

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 the aggregate retail investor, whereas Section V presents our empirical findings for different types of retail investors. Section VI provides our conclusions.

[5] For the volume-based order imbalance measure, our sample has a mean, median, and standard deviation of -0.01, 0.0, and 0.44, which is comparable to BJZZ’s values of -0.04, -0.03, and 0.46, respectively. For the trade-based order imbalance measure, our sample has a mean, median, and standard deviation of -0.04, 0.0, and 0.38, which is comparable to BJZZ’s values of -0.03, -0.01, and 0.44, respectively.

II. Nasdaq Helsinki and Related Literature

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

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 2 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 1 trillion euro. 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 of the German market.

*** Table 2 ***

Panel B of Table 2 shows that the average number of Finnish stocks traded per day during our sample is 121 compared to 3,000 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 C of Table 2 reports average trade size at selected benchmark years for Nasdaq Helsinki and the U.S. Nasdaq. In 2022, we find that the average trade size for Finnish stocks is 385 shares, which is much larger than the 149 average trade size for Nasdaq-listed (Tape C)

securities aggregated across all trading venues[6]. Average execution size declines sharply in both countries 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% of its stock 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

This study is related to the large literature on the relationship between retail trading and return predictability. First, we describe the relevant studies that examine the behaviour of the aggregate retail investor with respect to informed trading, liquidity provision, and noise trading. For ease of comparison to our study, we give sample details and period examined for each paper. Second, we describe the studies that have examined retail investor heterogeneity. Third, we describe other relevant papers.

II.B.1 Aggregate retail investor

Informed traders: There are several papers that have found evidence that the aggregate retail investor is an informed trader. Kaniel, et. al (2012) examine NYSE stocks for the years 2000 to 2003 and finds that retail investor buying (selling) predicts positive (negative) excess returns on or after earning announcements. Half of these excess returns are found to be

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

attributable to public and private information trading, with the other half attributable to liquidity provision. Kelley and Tetlock (2013) examine NYSE/Nasdaq/Amex stocks for the period February 2003 to December 2007 and finds that net buying by retail investors positively predicts stock returns up to one year, with no evidence of return reversal. They also find that passive net buying is consistent with liquidity provision as it is negatively related with past returns. Barber, Odean, and Zhu (2008) examine NYSE/Nasdaq/Amex stocks for the period 1983 to 2000 and finds positive persistence in order flow and a positive relationship with next four-weeks stock returns.

Campbell, Ramadorai, and Schwartz (2009) examine NYSE stocks for the period 1993 to 2000 and finds that institutions (complement of retail traders) trade momentum (value) in the short-term and make short-term losses (profits), respectively. Their short-term results are consistent with ours, but their results for institutions making long-term profits (or conversely, retail traders make long-term losses) contradicts ours. BJZZ (2021) examine sub-penny prices of market orders reported to one of FINRA's Trade Reporting Facilities for the period 2010 to 2015. They propose an algorithmic methodology to identify and sign retail trades. Specifically, the fraction of the penny Z_{it} that is associated with the transaction price P_{it} is defined as Z_{it} = 100 * mod ($P_{it,}$ 0.01) for trades with exchange code "D" reported to FINRA's TRF. A retail buy is defined as Z_{it} between 0.6 and 1, whereas a retail sell is defined as Z_{it} between 0 and 0.4. Values between 0.4 and 0.6 are not assigned as they are likely to be orders from institutions. They find that retail traders are contrarian traders, their order flow is highly persistent, and that they can predict stock returns up to 12-weeks ahead. A long-short portfolio delivers significant positive returns for up to 12 weeks, with no mean reversal. Further, they find that short-term return predictability (one-week ahead) is driven by order flow persistence and private information and not from liquidity provision or public news sentiment.

Farrell, et. al (2022) examine stocks that have reports curated on the Seeking Alpha platform (crowd-sourced investment research from non-professional analysts) for the period 2016 to 2018. They find that the ability of retail traders to predict short-term returns (one-week) in the post report publication period is positive, although they find non-positive week returns in the longer term (five-weeks). Fedyk (2023) examines Robinhood investors for the period May 2018 to August 2020. She finds that such investors buy after extreme negative returns, significant positive sentiment expressed on the reddit thread r/WallStreetBets, and on corporate announcement and analyst reports. The stocks that they invest in are large-cap and growth stocks, rather than value and small-cap stocks. She finds that Robinhood investors earned an annualized alpha of 17%. Luo et. al (2025) examine stocks obtained from a large discount broker for the period 2010 to 2014.q2. They find that retail investors tend to trade as contrarians after large earnings surprises and price changes, which generates momentum (higher returns) and PEAD. McLean, Pontiff and Reilly (2025) examine retail traders for the period October 2010 to 2021 and finds that retail traders generate positive returns that is orthogonal to that earned by various stock return anomalies.

Liquidity providers: Many papers have found evidence for liquidity provision by retail traders. Chordia and Subrahmanyam (2004) examine NYSE stocks for the period 1983 to 1998 and find that retail order balances are autocorrelated. They also find that retail order imbalance is positively related to next day's returns and stock returns exhibit reversals over the next four days as the continued price pressure is reversed. Andrade, Chang and Seasholes (2008) examine Taiwanese stocks for the period 1994 to August 2002 and find that returns in this week is positively related with this week's retail order imbalance and is negatively related with last week's retail order imbalance (price reversal). Dorn, Huberman, and Sengmuller (2008) examine a randomly drawn sample of retail trades for a German discount broker for the period February 1998 to May 2000. They find that retail traders seem to place correlated trades, and

that market (limit) orders lead to positive two-day returns, and subsequently turns negative (positive), suggesting liquidity concerns. Kaniel, Saar, and Titman (2008) examine NYSE stocks for the period 2000 to 2003 and finds positive excess returns in the month following intense retail buying, and negative excess returns in the month following intense retail selling. The results suggest that risk-averse retail traders provide liquidity to institutional traders. Barrot, Kaniel, and Sraer (2016) examine French stocks for the period 2202 to 2010 and finds that retail investor trades are contrarian in nature. They also find that their ability to predict one-month stock returns is significantly enhanced during market stress when market liquidity provisions decline, but retail investors do not reap the rewards from providing this liquidity.

Noise traders: Many papers have found evidence that the aggregate retail investors are noise traders. Odean (1998) examines data from a large discount brokerage house for the years 1988 to 1996 and finds that retails investors suffer from the disposition effect, namely, sell winners too early and sell losers too late. He finds that a portfolio of winning stocks sold and paper losses of losing stocks not sold, would earn excess returns of 3.58% over the next two years. Grinblatt and Keloharju (2000) examine Finnish stocks for the two years 1995 and 1996 and finds that foreign investors follow momentum strategies, whereas domestic investors follow contrarian strategies. They also find that the six-month future excess returns are greater for foreign investors than that of domestic investors. In contrast, Swan and Westerholm (2006) examine Finnish stocks for the 10-year period 1995 to 2004 and finds that domestic investors outperform foreign investors when one examines the longer panel. Barber and Odean (2000) examines data from a large discount brokerage house for the six years 1991 to 1996 and finds evidence for overconfidence as retail investors who trade the most underperform investors who trade the least. Rf and Wu (2007) examine impact of the daily upper price limit imposed (a proxy for "attention grabbing" by the Shanghai Stock Exchange on Chinese stocks. They find that retail investors have more buy order imbalances on the day many stocks hit their upper

price limit ("event"). They also find that retail investors make negative excess returns when prices reverse in the six days after the event. Barber and Odean (2008) examines data from a large discount brokerage house for the six years 1991 to 1996 and finds that individual investors display attention-driven buying behavior as they are net buyers on: high-volume days, following extremely negative and extremely positive one-day returns, and when stocks are in the news.

Using small trades as a proxy for retail trading, Hvidkjaer (2008) examines NYSE/Amex stocks and finds that stocks heavily bought by retail investors over horizons ranging for one month to one year underperform stocks heavily sold by retail investors. Barber, et. al (2008) examine Taiwanese stocks for the five-year period 1995 to 1999 and finds that individual investors underperform by 3.8% annually. Barber, Odean, and Zhu (2009) examine NYSE/Nasdaq/Amex stocks for the period 1983 to 2000 and finds correlated and positive trading due to psychological investor biases. Linnainmaa (2010) examines Finnish stocks for the period September 1998 to October 2001 and finds that individual investors make negative intra-day returns after earnings announcements and exhibit the disposition effect. He also finds that some of these effects are driven by limit orders. Fong, Gallagher and Lee (2014) examine Australian stocks for the period 1995 to 1997 and find that retail trades made through discount and full-service brokers earn negative abnormal returns over the next six months. They also find that this effect is greater for discount brokers when compared to full-service brokers. Della Vedova, Grant and Westerholm (2023) examine Finnish stocks for the period 2000 to 2009 and finds that retail investors exhibit disposition effects around a stock's 52-week high (52WH) by selling limit orders five days before the 52WH which benefits institutional investors with higher excess returns in the post-52WH period.

II.B.2 Heterogenous retail investors

In this section we describe the literature that has found certain types of investors to have heterogeneous skill in performance and return predictability.

Location: Many papers have shown that investors choose to invest in companies who are located close to them (Grinblatt and Kelohorju, 2001; Huberman 2001). However, the evidence whether such local trading is more profitable for a local investor is mixed. Some studies have found positive performance due to informed trading by local investors (Coval and Moskowitz, 2001; Ivković and Weisbenner, 2005; Massa and Simonov, 2006; Bernile, et. al 2015; 2018), whereas other studies (Seasholes and Zhu, 2010; Doskelanda and Hvide, 2011) finds non-positive abnormal returns.

Age: On the one hand, studies have shown that older investors earn positive excess returns because of their learned experience in stock trading (List, 2003; Feng and Seasholes, 2005; Goetzmann and Kumar, 2008, Chen, Liang, and Shi, 2022). Older investors have also been shown to possess lower behavioural biases such as a weak disposition effect (Dhar and Zhu, 2006), a lower degree of overconfidence (Barber and Odean, 2001), hold less-concentrated portfolios (Goetzmann and Kumar, 2008), and invest less in lottery-type stocks (Kumar, 2009). On the other hand, Korniotos and Kumar (2011) find that older investors have worse return performance because the negative cognitive effect of ageing dominates the positive effects of investor experience.

Sophistication: The prior literature has found that investor sophistication affects trading performance and stock market participation, with less sophisticated investors exhibiting lower performance and stock market participation (Barber and Odean, 2000; Grinblatt and Keloharju, 2001; Grinblatt, Keloharju, and Linnainmaa, 2011, 2012; Barber et. al, 2014; Campbell,

Ramadorai, and Ranish, 2019; Eaton, Green, Roseman, and Wu, 2022; Kaniel et. al, 2023; and Jones et. al, 2025).

Gender: Many studies have shown that female investors are more risk averse and less overconfident than their male counterparts. But the evidence for whether male or female investors have superior investment performance is mixed. Using US data from a brokerage firm for the six years 1990 to 1996, Barber and Odean (2001) find that males trade more, and underperform more than females. In contrast, using Finnish data for the 20-years 1995 to 2014, Wu and Westerholm (2014) find that female investors diversify less, and earn higher returns, than male investors.

II.B.4 Other relevant literature

Studies that criticize BJZZ: Barber et al. (2024) placed 85,000 retail trades in six retail brokerage accounts from December 2021 to June 2022. They find that the BJZZ algorithm correctly identifies only 35% of the placed trades as retail (Type-II errors), incorrectly signs whether it is a buy or a sell order for 28% of the placed trades and provides uninformative order imbalance measures for 30% of the stocks. If the authors instead use the quote midpoint method, they find the same misidentification rate, but a reduction in the signing error rates to 5%, and informative order imbalance measures for all stocks.

Battalio et al. (2024) examines three proprietary datasets. The first dataset consists of over 53 million trades generated by over 40 million retail marketable orders executed by one or more wholesalers in May 2022. After matching this sample to TAQ/TRF, they find that almost 40.5% of the matched trades have execution prices that have no sub-penny prices and roughly 32% of the matched trades have trades that have a sub-penny price in the interval [0.4, 0.6] -- and are therefore not identified as retail trades by BJZZ. As a result, less than 28% of the sample of known retail trades are classified as retail by the BJZZ methodology (Type-II errors). Using two separate data sets of institutional trades, the paper also shows many

institutional trades being classified as retail by the BJZZ methodology (Type-I errors). In sum, the above two papers show that the BJZZ methodology does a partial job in identifying retail trading.

Ardia, Aymard, and Cenesizoglu (2024) examine the same sample as BJZZ but extent it from 2016 to 2021. Using the BJZZ methodology they confirm the strong return predictability of retail order imbalance in BJZZ's sample period of 2010 to 2015. But they find that the return predictability is much leaker in the 2016 to 2021 period. They also find that the long-short portfolio is no longer profitable across all stocks and significantly less profitable for small stocks They conclude that their results indicate either a substantial weakening or a disappearance of most of BJZZ's main findings in the recent 2016 to 2021 period.

Other studies that use Finnish data: We have explained in Section II above, many studies that have utilized Finnish data. There are three additional studies. First, Lepone, Westerholm and Wright (2023) find that individuals who have had good experiences such as high GDP growth and low divorce rate during adolescence are more likely to invest in speculative stocks that earn lower returns. Second, Pitkajarvi and Vacca (2024) examines option trading on Finnish stocks and finds that the disposition effect of selling winners too quickly and holding on to losers is more pronounced in options than in stocks. Vacca (2026) finds that some firm rank and file employees purchase options on their employers' stock which earns 60 basis points around earnings announcements.

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 buy order imbalances 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 retail 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 3. 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 25^{th} and 75^{th} 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 3 ***

IV. Empirical Tests and Results for the Aggregate Retail Investor

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 buy 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 buy 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 4. In the first column where we use volume-based retail order imbalance as the dependent variable, the coefficient on past week retail 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 retail 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 retail order imbalance as the dependent variable.

*** Table 4 ***

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 buy order imbalances and short-term (one-week) 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:

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

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 buy 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 imbalance is largely uninformative for future stock returns.

The estimation results for predictive equation (2) are reported in Table 5. In the first column, when we include $oib_{i,w-1}$, measured as past week's retail 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 each 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 imbalances suggests that our results are not driven by trade size.

*** Table 5 ***

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, the above results indicate that the aggregate retail order flow is informative about the cross-section of stock returns over short horizons.

IV.C Retail buy order imbalances 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 buy order imbalances predict 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 6. For volume-based buy order imbalances, 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 buy order imbalances. Overall, these patterns suggest that the observed return predictability of the average retail investor is long-term (15-week).

*** Table 6 ***

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 buy order imbalances 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 15 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 7. The estimated coefficient on volume-based buy order imbalances 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 retail order imbalance 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 7 ***

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 Tables 1A.1 and 1A2 of the Appendix, we show that all our main predictability results remain virtually unchanged when Nokia is excluded from the sample.

*** Appendix: Tables 1A.1, 1A2 ***

Taken together, the k-week ahead regressions and the 15-week 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 significance and trading strategy implications

The long-term predictive power of retail order flows documented above raises the question of whether their information content can be exploited in a profitable trading strategy. If retail order imbalance contains information about future prices, one would expect that stocks with high recent buying pressure to outperform those with high selling pressure. To test this hypothesis, we use past order imbalance as a signal and sort stocks each day into tercile based on their previous week's order imbalance. Specifically, we form an equally weighted long-short portfolio that buys stocks in the top tercile and shorts stocks in the bottom tercile and calculate buy-and-hold tercile portfolio returns over holding horizons of one to fifteen weeks. The portfolios are carried through the look-ahead return measurement horizon by following a buy-and-hold strategy. This strategy results in overlapping windows that adds to the statistical

power for multiperiod portfolio returns (Richardson and Smith, 1991). We adjust the standard errors of portfolio returns using Hansen and Hodrick (1980).

The performance results are reported in Table 8. The long-short portfolio based on volume-based order imbalance is reported in Panel A and delivers a return of 0.249% over a 5-day horizon (week). Risk adjustment using the Fama-French four-factor model results in an alpha of 0.257% over a horizon of five days, suggesting that the return spread is not explained by standard factor exposure. While average returns and alphas decline with the holding horizon, they remain positive and statistically significant even at longer horizons. Importantly, we find no evidence of return reversals, consistent with persistent information content in retail order imbalance. The pattern in Panel B where the long-short portfolio is based on the number of trade-based retail order imbalance is similar.[7]

*** Table 8 ***

IV.E Economic mechanisms behind long-term stock return predictability

Having established that retail order imbalance predicts a positive relationship with both weekly and 15-week cumulative future stock returns, we next examine the underlying economic mechanisms for this long-term return predictability. The above results are consistent with retail traders having good information and not for the liquidity provision and noise trader hypotheses. 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. The BJZZ methodology allows us to separate retail buy order imbalances into components associated with persistence, contrarian trading, public news sentiment, and a residual component orthogonal to these channels (private information).

[7] Note that execution costs and order-handling frictions can materially affect realizable performance of retail-style strategies (Anand et al., 2025; Schwarz et al., 2025).

To obtain a public news sentiment measure, 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[8]. The database provides key information about each news/event item, such as ISIN, the date/timestamp of announcement, the news headline, 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[9]. We then 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, we decompose weekly buy order imbalances into four components. Specifically, each trading day, we estimate the following cross-sectional regression using weekly (5-day) variables:

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

[8] 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.

[9] Chen et al., 2025 use GPT-4 Turbo on social media data to classify trading strategies of retail investors and find that retail traders' strategy adoption responds to news.

Following BJZZ, $\text{sent}_{i,w-1}$ 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:

$$\widehat{persistence}_{i,w-1} = \widehat{e1_{i,w-1}}\text{oib}_{i,w-2}$$

$$\widehat{\text{contrarian}}_{i,w-1} = \widehat{e2'_{i,w-1}}\text{Ret}_{i,w-2}$$

$$\widehat{publicnews}_{i,w-1} = \widehat{e3_{i,w-1}}\text{sent}_{i,w-1}$$

$$\widehat{other}_{i,w-1} = \widehat{e0_{i,w-1}} + \widehat{u3_{i,w-1}}$$

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.

$$ret_{i,w:w+14} = f0_w + f1_w\widehat{\text{persistence}}_{i,w-1} + f2_w\widehat{\text{contrarian}}_{i,w-1} + f3_w\widehat{\text{other}}_{i,w-1} + f4'_w\text{Ret}_{i,w-1} + f5_w\widehat{publicnews}_{i,w-1} + u4_{i,w+1:w+14}$$

The results are reported in Table 9. 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 behaviors. Our results are like those found in BJZZ.

*** Table 9***

We report the second-stage decomposition results in Panel B of Table 9. For volume-based buy order imbalances reported in column (1), both the persistence and private

information 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 private information 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-term return predictability.[10] 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 private information not captured by the measured public news releases. Economically, moving from the 25th to the 75th percentile of private information 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 private information 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 retail order imbalance measure. Persistence and the private information 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 buy order imbalances is consistent with an information-based channel operating

[10] 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.

through sustained trading and private information, that is orthogonal to observable public news, rather than through transient liquidity provision or better interpretation of public news.

IV.E Stability of results over time

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 10. 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 retail order imbalance and trade-based retail 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 retail order imbalance and 0.0078 (t-stat = 5.46) for trade-based buy 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 buy order imbalance; if anything, the trade-count-based measure delivers the largest spread in the most recent period.[11]

*** Table 10 ***

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 stock returns in the most recent years of our sample, alleviating concerns that the documented predictability is an artefact of a specific historical episode.

V. Empirical Tests and Results for Heterogeneous 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, wealth, education, sophistication, and gender influence stock market participation, portfolio choice, and investment performance (Campbell, 2006; Guiso and Sodini, 2013; Bach, Calvet and Sondini, 2020; Gomes, Haliassos, and Ramadorai, 2021; Balasubramaniam, et. al, 2025; Betermier et. al, 2025; Giglio, et. al, 2025; and Campbell and Ramadorai, 2025). If these differences are systematic, one might expect return predictability to vary across investor characteristics.

Before turning to specific dimensions of heterogeneity, we first examine whether our baseline long-term return 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

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

excluding their trades alters the predictive power of aggregate retail buy order imbalance. To test this, we estimate equation (4) by using retail buy order imbalances adjusted to exclude insiders' and brokers' trades. The results are reported in Table 11. The coefficients on the insider- and broker-adjusted retail order imbalance remain positive, statistically significant, and similar in magnitude to those reported in Table 5. This suggests that our main predictability results are not an artefact of insider/brokers' activity being misclassified as retail trading.

*** Table 11 ***

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 Local and distant investors

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 (km) for the closest tercile, 137 (145) km for the middle tercile, and 385 (341) km 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 buy order imbalances for each distance tercile and jointly examine their ability to predict stock returns by estimating equation (4).

Column (1) of Table 12 reports the estimation results for volume-based order imbalance. The coefficient on the retail 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. Formal Wald tests reject equality between the coefficients for local and most distant investors at conventional levels, while failing to reject equality between the coefficients for the two more distant groups. 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 retail order imbalance is measured using the number of trades, with local order flow continuing to exhibit the strongest predictive power.

*** Table 12 ***

Over a period of 15-weeks, long-short portfolio returns in Panel A of Table 1A.3 of the Appendix shows that buy-and-hold returns and 4-factor alphas of long-short portfolio of local investors yield 1.038% and 1.364%, respectively. The corresponding returns for non-local investors are of smaller magnitudes. For example, 4-factor alpha on long-short portfolio of investors in distance tercile 2 and 3 are 0.835% and 0.907%, respectively.

*** Appendix: Panel A of Table 1A.3 ***

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 Investor age groups

The second dimension of heterogeneity we examine is investor age. Prior work shows that age is associated with differences in risk-taking, trading behavior, 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 reports 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 retail order imbalance of one age group at a time along with our standard controls. The results are reported in Table 13, with Panel A for volume-based buy order imbalances, and Panel B for trade-based buy order imbalances. Columns (1) to (5) in Panel A show that buy order imbalances for all age groups have positive and statistically significant coefficients when considered in isolation. However, the magnitude of return predictability varies non-linearly with age. Predictive power increases from the youngest group, peaks for investors aged 26–40, and then declines monotonically for older cohorts, with the weakest effects observed for investors older than 68. Moving from the 25th percentile to the 75th percentile of retail order imbalance for the 26–40 age group results in a 1.1% increase in 15-week cumulative returns.

*** Table 13 ***

To distinguish which age cohorts' matter once we control for trading of other cohorts, we then estimate a joint regression where we include the buy order imbalances of all age groups simultaneously. Column (6) in Panel A reports the joint estimation and confirms a hump-shaped pattern in return predictability across age groups. Predictive power is strongest for prime-age investors (26–40 and 41–55) and declines for both younger and older cohorts. In contrast, the coefficient on the order imbalances of investors past retirement age shrinks substantially and is no longer statistically significant in the joint estimation. The patterns in Panel B that reports estimation results for the 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). Taken together, these results indicate a non-linear, hump-shaped relationship between investor age and the information content of retail trades, with predictability concentrated among prime-age investors.

We report long-short portfolio returns in Panel B of Appendix IA.3 for each age groups following the long-short portfolio approach discussed in section IV.C. Oover a horizon of 15-weeks, a trading strategy following the long-short portfolio of investors in age group 26-40 years earn buy-and-hold returns and 4-factor alphas of 1.286% and 1.668%, respectively. The returns for the portfolios of other age groups are smaller. These results are consistent with the patterns observed in the Fama-Macbeth regressions in Table 13.

*** Appendix: Panel B of Table 1A.3 ***

V.C Sophisticated and naive investors

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; Grinblatt and Keloharju,

2000; Gargano and Rossi, 2018[12]; Campbell, Ramadorai, and Ranish, 2019; Eaton, Green, Roseman, and Wu, 2022; and Jones et. al, 2025). One would therefore expect that trades of financially sophisticated investors to have a stronger predictive power for the cross-section of stock returns.

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 centre. 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).

Table 14 presents the results. Column (1), which reports estimation results for volume-based buy order imbalances shows that the coefficient on the retail order imbalance of sophisticated investors is 0.0052 (t-stat=8.5), whereas the coefficient on naïve retail order imbalance is substantially smaller at 0.0024 (t-stat=2.98). The difference between the coefficients for Helsinki-based and non-Helsinki investors is statistically significant, as equality between the two coefficients is rejected using two-sided Wald tests. 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 retail order imbalance is measured using the number of trades, as reported in column (2).

*** Table 14 ***

The long-short portfolio returns on Helsinki and non-Helsinki investor groups are reported in Panel C of Table IA.3 of the Appendix Consistent with the results in Table 14, the

[12] Gargano and Rossi (2018) find that high-attention investors who buy high-attention stocks earn positive returns that persists over six months.

long-short portfolio of Helsinki investors delivers buy-and-hold returns and 4-factor alpha of 1.388% and 1.718%, respectively. In contrast, the performance of the non-Helsinki portfolio is smaller, for example, buy-and-hold returns and 4-factor alpha are 0.542% and 0.870%, respectively.

*** Appendix: Panel C of Table 1A.3 ***

Taken together, both proxies for sophistication indicate that return predictability is higher in the trading activity of more sophisticated retail investors. These results are consistent with those found in Barber and Odean (2000), Grinblatt and Keloharju (2000), Gargano and Rossi (2018), Campbell, Ramadorai, and Ranish (2019), Eaton et al. (2022), and Jones et. al, (2025).

V.D Investor gender

The fourth dimension of heterogeneity we examine is gender. Prior evidence documents that men trade more than women and that their 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 buy 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 15. 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. Formal Wald tests reject equality between the coefficients on

male and female order imbalances, indicating that return predictability is significantly stronger for trades placed by male investors. 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 the number of trade-based order imbalance in column (2).

*** Table 15 ***

The long-short portfolio returns on male and female investors are reported in Panel D of Table 1A.3 of the Appendix. Consistent with the results in Table 15, the long-short portfolio for male investors delivers buy-and-hold returns and 4-factor alphas of 0.973% and 1.430%, respectively. In contrast, the performance of the female portfolio is smaller.

*** Appendix: Panel D of Table 1A.3 ***

These portfolio results indicate that male investors' order flow has stronger predictive content for the cross-section of future returns and is consistent with what we found using our Fama-Macbeth regressions. While prior work shows that excessive trading reduces individual portfolio performance for male investors (Barber and Odean, 2001), our analysis focuses on the informational content of aggregate order flow rather than realized portfolio performance at the individual level. Our findings therefore speak to differences in the information embedded in male and female order flow, rather than differences in net returns earned by individual investors.

VI. Conclusions

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 does not suffer from mismeasurement problems that arise when retail trades or traders must be inferred from brokerage houses(s) or trade-classification algorithms. We show that the aggregate retail order imbalance predicts the cross-section of stock returns over horizons up to several weeks (15-weeks), and that this predictability is consistent with retail investors having private information, which they use in order splitting to hide their private information channel, rather than short-lived liquidity provision or noise trading. The predictive power of retail order imbalance 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 imbalance is higher among local investors, working-age investors, more sophisticated investors, as well as men. Return predictability is weaker for distant, older, less sophisticated investors, and females, suggesting substantial heterogeneity in how retail trading contributes to price discovery.

References

Anand, Amber, Mehrdad Samadi, Jonathan Sokobin, and Kumar Venkataraman, 2025, Retail limit orders. *Review of Finance*. Forthcoming

Andrade, Sandro C., Charles Chang, and Mark S. Seasholes, 2008. Trading imbalances, predictable reversals, and cross-stock price pressure, *Journal of Financial Economics* 88, 406–423.

Ardia, David, Clement Aymard, and Tolga, Cenesizoglu, 2024, Revisiting Boehmer et al. (2021): Recent period, alternative method, different conclusions, Working paper.

Bach, Laurent, Laurent Calvet, and Paolo Sodini, 2020, Rich pickings? Risk, return, and skill in household wealth, *American Economic Review* 110, 2703-2747.

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

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

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

Barber, Brad, Yi-Tsung Lee, Yu-Jane Liu, and Terrance Odean, 2008, Just how much do individual investors lose by trading? *Review of Financial Studies* 22, 609–632.

Barber, Brad, Terrance Odean, and Ning Zhu, 2008, Do retail trades move markets? *Review of Financial Studies* 22, 151−186.

Barber, Brad, Terrance Odean, and Ning Zhu, 2009, Systematic noise, *Journal of Financial Markets* 12, 547−569.

Barber, Brad, Yi-Tsung Lee, Yu-Jane Liu, and Terrance Odean. 2014. The cross-section of speculator skill: Evidence from day trading, *Journal of Financial Markets* 18, 1–24.

Barber, Brad, Shengle Lin, and Terrance Odean, 2023, Resolving a paradox: Retail trades positively predict returns but are not profitable, *Journal of Financial and Quantitative Analysis* 59, 1-35.

Barber, Brad, 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, 2403–2427.

Barrot, Jean-Noel, Ron Kaniel, and David 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.

Bernile, Gennaro, Alok Kumar, and Johan Suleman, 2015, Geography of information and local investors, *Review of Financial Studies* 28, 2009–2049.

Bernile, Gennaro, Alok Kumar, Johan Suleman and Qin Wang, 2019, Has local informational advantage disappeared? *Review of Financial Economics* 37, 38–60.

Betermier, Sebastien, Laurent Calvet, Samuli Knupfer, and Jense Kvaerner, 2025, Investor factors, *Journal of Finance* 0, 1-41.

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

Campbell John, 2006, Household finance, *Journal of Finance* 61, 1553-1604.

Campbell, John, Tarun Ramadorai, and Allie Schwartz, 2009, Caught on tape: Institutional trading, stock returns, and earnings announcements, *Journal of Financial Economics* 92, 66-91.

Campbell, John, Tarun Ramadorai, and B. Ranish, 2019, Do the rich get richer in the stock market? Evidence from India, *American Economic Review: Insights* 1, 225–240.

Campbell, John, and Tarun Ramadorai, 2025, Household finance in retrospect and prospect, Working paper.

Calvet, Laurent, John C. Campbell, Francisco Gomes, and Paolo Sodini, 2025, The cross-section of household preferences, Working paper.

Chen, Weihua, Shushu Liang, and Donghui Shi, 2022, Who chases returns*?* Evidence from the Chinese stock market, Working paper.

Chen, Shuaiyu, Lin Peng, and Dexin Zhou, 2025, Wisdom or whims? Decoding retail strategies with social media and ai, Working paper.

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

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

Coval, Joshua, David Hirshleifer, and Tyler Shumway, 2021, Can individual investors beat the market?, *Review of Asset Pricing Studies* 11, 552-579

Della Vedova, Joshua, Andrew Grant and Joakim Westerholm, 2023, Investor Behavior at the 52-Week High, *Journal of Financial and Quantitative Analysis* 58, 2852–2889.

Dhar, Ravi, and Ning Zhu, 2006, Up close and personal: Investor sophistication and the Disposition Effect, *Management Science* 52, 726-740.

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

Doskeland, Trond, and Hans Hvide, 2011, Do individual investors have asymmetric information based on work experience, *Journal of Finance* 66, 1011-1041.

Eaton, Gregory, Clifton Green, Brian Roseman, and Yanbin Wu, 2022, Retail trader sophistication and stock market quality: Evidence from brokerage outages, *Journal of Financial Economics* 146, 502–528.

Farrell, Michael, Clifton Green, Russell Jame, and Stanimir Markov, 2022, The democratization of investment research and the informativeness of retail investor trading, *Journal of Financial Economics* 145, 616-641.

Fedyk, Valeria, 2022, This time is different: Investing in the age of Robinhood, Working paper.

Feng, Lei, and Mark Seasholes, 2005, Do investor sophistication and trading experience eliminate behavioral biases in financial markets? *Review of Finance* 9, 305–351.

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

Gargano, Antonio and Alberto Rossi, 2018, Does it pay to pay attention? *Review of Financial Studies* 31, 4595–4649.

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

Giglio, Stefano, Matteo Maggiori, Johannes Stroebel, and Stephen Utkus, 2021, *American Economic* Review, 111, 1481-1522.

Grinblatt, Michael, and Matti Keloharju, 2000, The investment behavior and performance of various investor types: A study of Finland's unique data set, *Journal of Financial Economics* 55, 43–67.

Grinblatt, Michael, and Matti Keloharju, 2001, How distance, language, and culture influence stockholdings and trades, *Journal of Finance* 56, 1053–1073.

Grinblatt, Michael, Matti Keloharju, and Juhani Linnainmaa, 2011, IQ and stock market participation, *Journal of Finance* 66, 2121–2164.

Grinblatt, Michael, Matti Keloharju, and Juhani Linnainmaa, 2012, IQ, trading behavior, and performance, *Journal of Financial Economics* 104, 339–362.

Goetzmann, William, and Alok Kumar, 2008, Equity portfolio diversification, *Review of Finance* 12, 433–463.

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*, 2, North Holland, New York.

Gurrola Perez, Pedro, Lin, Kaitao and B. Speth, 2022, Retail trading: An analysis of current trends and drivers, Working paper.

Huberman, Gur, 2001, Familiarity breeds investment, *Journal of Finance* 14, 659-680.

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

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, Zihan Lin, Markus Pelger, and Stijn Van Nieuwerburgh, 2023, Machine- learning the skill of mutual fund managers, *Journal of Financial Economics* 150, 94-138.

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

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

Kumar, Alok, 2009, Who gambles in the stock market? *Journal of Finance* 64, 1889–1933.

Laarits, Thomas and Marco Sammon, 2025, The retail habitat, *Journal of Financial Economics*, 10, 41-44.

Lepone, Grace, Joakim Westerholm, and Danika Wright, 2023, Speculative trading preferences of retail investor birth, *Accounting & Finance* 63, 555-574.

Linnainmaa, Juhani, 2010, Do limit orders alter inferences about investor performance and behavior? *The Journal of Finance*, 1473-1506.

List, John, 2003, Does market experience eliminate market anomalies? *Quarterly Journal of Economics* 118, 41–71

Luo, Cheng (Patrick), Enrichetta Ravina, Marco Sammon, and Luis Viceira. 2025. Retail investors' contrarian behavior around news, attention, and the momentum effect, Working paper.

Massa, Massimo, and Andrei Simonov, 2006, Hedging, familiarity and portfolio choice, *Review of Financial Studies* 19, 633685.-

McLean, David, Jeffrey Pontiff, and Christopher Reilly, 2025, Taking sides on return predictability, *Journal of Financial Economics,* 104-158

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

Odean, Terrance, 1998, Are investors reluctant to realize their losses? *Journal of Finance* 53, 1775–1798.

Pitkajarvi, Aleksi and Matteo Vacca, 2024, Striking out: Biases and losses of retail option traders, Working paper.

Richardson, M and T. Smith, 1991, Tests of Financial Models in the Presence of Overlapping Observations. *Review of Financial Studies* 4 , 227–254.

Seasholes, Mark, and Guojun Wu, 2007, Predictable behavior, profits, and attention. *Journal of Empirical Finance* 14, 590–610.

Seasholes, Mark, and Ning Zhu, 2010, individual investors and local bias, *Journal of Finance* 65, 1987–2010.

Swan, Peter and Joakim Westerholm, 2006, Are domestic household investors better performers than foreign institutions? New evidence from Finland, in Itzhak Venezia (ed) *Behavioral* Finance: Chapter 4, World Scientific Publishing Co., Singapore.

Schwarz, Christopher, Brad Barber, Xing Huang, Philippe Jorion, and Terrance Odean, 2025, The "actual retail price" of equity trades. *Journal of Finance* 80, 2507-2541.

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

Vacca, Matteo, 2026Insider trading with options: Evidence from rank-and-file employees, *Journal of Corporate Finance* 98, 1–21.

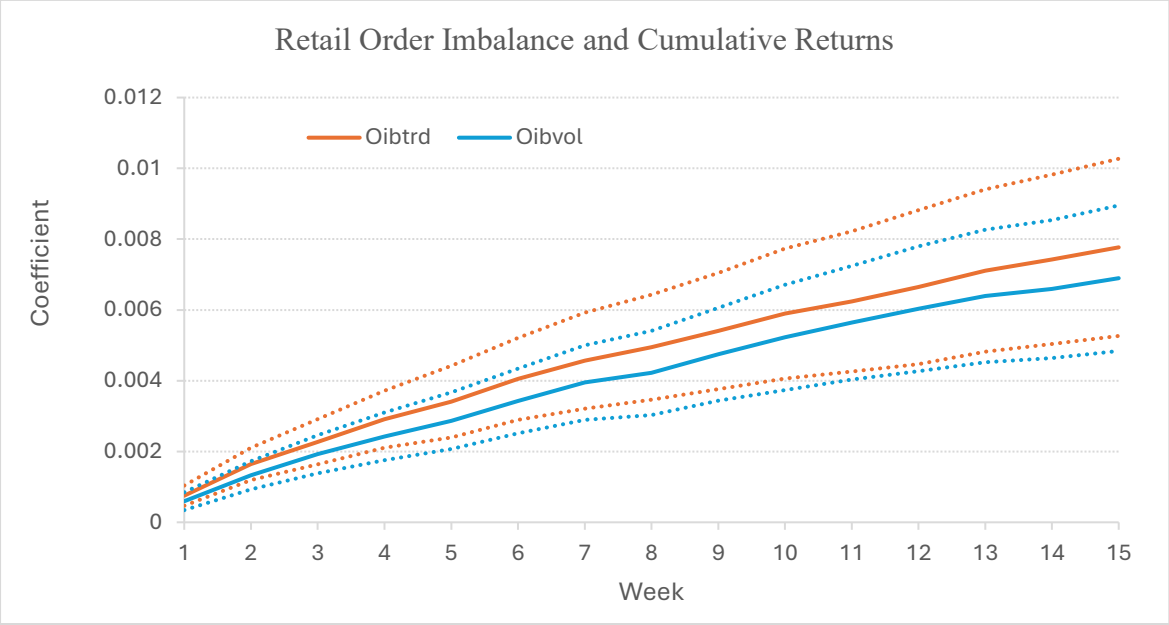
Welch, Ivo, 2022. The wisdom of the Robinhood crowd, *Journal of Finance* 77, 1489–1527.

Wu, Zheng and Joakim Westerholm, 2024, Gender differences in equity portfolio diversification, *Pacific-Basin Finance Journal* 88*,*1-21.

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*

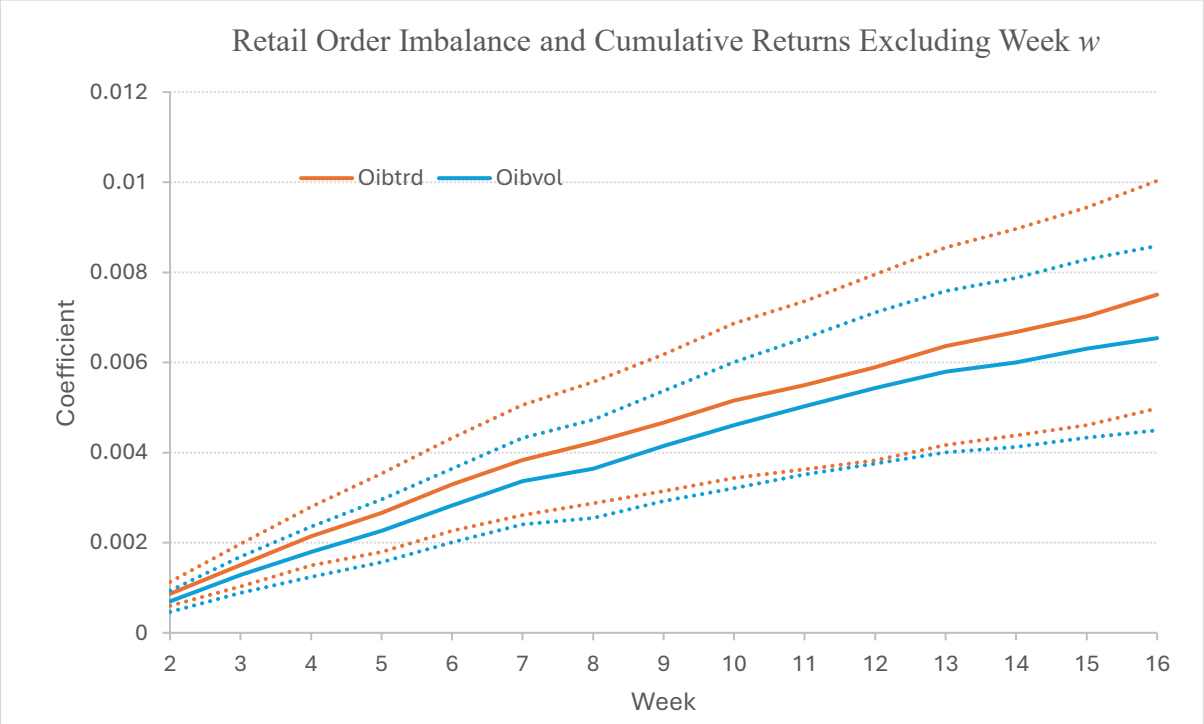


Table 1: Expected Relationship Under the Various Retail Trader Hypotheses

This table summarizes the expected signs of key empirical relationships predicted by three competing retail trader hypotheses. For each hypothesis, the table reports predicted signs for persistence in retail order flow, its relationship with lagged stock returns, and short-term and long-term return predictability and excess returns associated with retail order imbalance. Persistence in order flow is common across hypotheses but reflects different underlying mechanisms and is therefore not sufficient on its own to distinguish between trader types. Differences across hypotheses arise from how retail order imbalance relates to past returns and from the horizon over which return predictability and excess returns are expected to occur.

Retail Trader Hypotheses	Persistent Order Flow	Relationship with lagged stock returns	Short-Term Return Predictability and Excess Returns	Long -Term Return Predictability and Excess Returns
Informed retail trader	+ (strategic order splitting to reduce price impact and conceal valuable information)	- (trading against recent price movements due to information about mispricing)	+	+
Liquidity-providing retail trader	+ (liquidity provision to institutional order splitting)	0 (order flow driven by institutional liquidity demand, not past returns)	+	0, -
Noise-trading retail trader	+ (gradual trading due to behavioural biases such as overconfidence, disposition effect, and persistent sentiment)	+ (return chasing and attention-driven trading)	0,-	0, -

Table 2: Characteristics of Various Exchanges Across the World

This table reports descriptive statistics on exchange size and trading characteristics across selected equity markets. Panel A reports total equity value traded in 2022 for major exchange groups in the U.S. and Europe, sourced from the World Federation of Exchanges (statistics accessed 20 November 2025). Panel B reports measures of market activity, including the average number of unique stocks traded per day and aggregate daily trading volume measured in shares, for Finland and the U.S. Panel C reports average trade size, measured as the number of shares per trade, for Finland (Nasdaq Helsinki) and the U.S. (Nasdaq-listed stocks across all venues) in selected years.

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: Market breadth and trading volume

Average number of unique stocks traded per day (Finland)	121
Average number of unique stocks traded per day (U.S.)	3,000
Average daily trading volume (shares), Finland	65 million
Average daily trading volume (shares), U.S. Nasdaq	2.5 billion

Panel C: Average trade size in shares

	2002	2012	2022	Percent change 2002-2022
Finland (Nasdaq Helsinki)	4,491	857	385	-91%
U.S. (Nasdaq-listed, all venues)[13]	735	249	149	-80%

[13] 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 3: 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 4: Determinants of Retail Buty 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 retail 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). t-statistics based on Newey–West adjusted standard errors are reported in parentheses.

	(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 5: Retail Buy Order Imbalances and Short-Term (1-Week) 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). t-statistics based on Newey–West adjusted standard errors are reported in parentheses.

	(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 6: Retail Buy Order Imbalances 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). t-statistics based on Newey–West adjusted standard errors are reported in parentheses. Control variables are the same as in Table 5 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 7: Retail Buy Order Imbalances and 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). t-statistics based on Newey–West adjusted standard errors are reported in parentheses.

Dependent variable:	(1) 15-Week Cum. Return	(2) 15-Week Cum. Return	(3) 15-Week Cum. Return	(4) 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 8: Long-Short Portfolio Returns Based on Retail Order Imbalances

This table reports buy-and-hold portfolio raw returns and risk-adjusted returns based on a long–short strategy that buys stocks in the highest tercile of retail order imbalance and shorts stocks in the lowest tercile. Our sample period is January 1997 to December 2022 and our sample firms are common stocks from Finland. Portfolio returns are equally weighted. We report both mean buy-and-hold returns and risk-adjusted returns using the Fama-French four-factor model. As our data are overlapping, we adjust the standard errors of the portfolio return time series using Hansen-Hodrick (1980) standard errors with the corresponding number of overlapping lags.

Panel A: Portfolios are formed based on volume-based retail order imbalance

Holding period	Means	t-stat	Alpha	t-stat
1 week	0.249%	5.58	0.257%	5.95
2 weeks	0.397%	4.79	0.423%	5.31
4 weeks	0.550%	3.65	0.648%	4.59
6 weeks	0.696%	3.36	0.884%	4.62
8 weeks	0.803%	3.08	1.042%	4.35
10 weeks	0.877%	2.85	1.107%	3.83
12 weeks	0.915%	2.59	1.213%	3.66
15 weeks	0.989%	2.37	1.382%	3.51

Panel B: Portfolios are formed based on number of trade-based retail order imbalance

Holding period	Means	t-stat	Alpha	t-stat
1 week	0.272%	5.83	0.269%	6.07
2 weeks	0.444%	5.30	0.452%	5.62
4 weeks	0.644%	4.09	0.701%	4.79
6 weeks	0.805%	3.60	0.919%	4.49
8 weeks	0.9271%	3.29	1.050%	4.05
10 weeks	0.985%	2.92	1.075%	3.36
12 weeks	1.037%	2.66	1.155%	3.10
15 weeks	1.115%	2.42	1.230%	2.73

Table 9: Predictability Decomposition of Long-Term Stock Returns

This table reports estimation results on a decomposition of the predictive power of retail buy order imbalances 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 the retail 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 (GPT5-nano) using 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, public news, 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 retail order imbalance measures are decomposed into four components as specified above. Panel B reports the second-stage decomposition of buy order imbalance's predictive power, as specified above. Reported p-values correspond to two-sided Wald tests of equality between Fama–MacBeth coefficients. 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 retail order imbalance and reflects price pressure. The variable *oib(w−1, contrarian)* is estimated in the first stage using past returns over different horizons. 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). t-statistics based on Newey–West adjusted standard errors are reported in parentheses.

Panel A: First Stage of Projecting Retail 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 Buy 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%
p-values (pers = other)	0.06	0.02

Table 10: Retail Buy Order Imbalances and 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). t-statistics based on Newey–West adjusted standard errors are reported in parentheses.

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%

Table 11: Retail Buy Order Imbalances and 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). Retail 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). Retail 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). t-statistics based on Newey–West adjusted standard errors are reported in parentheses.

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 12: Predicting Long-Term Stock Returns Using Retail Buy Order Imbalances 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). Reported p-values correspond to two-sided Wald tests of equality between Fama–MacBeth coefficients. t-statistics based on Newey–West adjusted standard errors are reported in parentheses.

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%
p-values (oib1=oib3)	0.04	0.09
p-values (oib1=oib2)	0.05	0.09
p-values (oib2 = oib3)	0.80	0.89

Table 13: Predicting Long-Term Stock Returns Using Retail Buy Order Imbalances of Different 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 buy order imbalances 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 retail order imbalance whereas Panel B reports estimation results for trade-based buy order imbalance. Columns (1)–(5) include retail order imbalance for one age group at a time; Column (6) includes buy 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). t-statistics based on Newey–West adjusted standard errors are reported in parentheses.

Panel A: Predicting Cumulative Long-Term Stock Returns Using *Volume-Based* Order Imbalances						
	(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 diff.	0.6732%	1.110%	0.8025%	0.6908%	0.3547%	

Panel B: Predicting Long-Term Stock Returns Using Number of *Trades-Based* Order Imbalances						
	(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** (2.07)	-0.0002 (-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 diff.	0.6757%	1.0724%	0.9022%	0.7076%	0.3924%	

Table 14: Predicting Long-Term Stock Returns Using Retail Buy Order Imbalances 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. We classify investors 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 retail 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). Reported p-values correspond to two-sided Wald tests of equality between Fama–MacBeth coefficients. t-statistics based on Newey–West adjusted standard errors are reported in parentheses.

Dependent variable:	(1) 15-Week Cumulative Return	(2) 15-Week Cumulative 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%
p-values (oib, Helsinki = oib, Other)	0.005	0.004

Table 15: Predicting Long-Term Stock Returns Using Retail Buy Order Imbalances 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 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 buy order imbalances 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). Reported p-values correspond to two-sided Wald tests of equality between Fama–MacBeth coefficients. t-statistics based on Newey–West adjusted standard errors are reported in parentheses.

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%
p-values (Oib, Female = oib, Male)	0.0003	0.0002

APPENDIX

Table IA.1: Retail Buy Order Imbalances 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). t-statistics based on Newey–West adjusted standard errors are reported in parentheses.

	(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 Buy Order Imbalances and 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). t-statistics based on Newey–West adjusted standard errors are reported in parentheses.

	(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

Table IA.3: Long-Short Portfolio Returns Based on Retail Order Imbalances for Heterogeneous Investor Groups

This table reports buy-and-hold portfolio raw returns and risk-adjusted returns (in percent) based on a long–short strategy that buys stocks in the highest tercile of retail order imbalance and shorts stocks in the lowest tercile, constructed separately for each heterogeneous investor group. Risk-adjusted returns are computed using the. Our sample period is January 1997 to December 2022, and our sample firms are common stocks from Finland. Portfolio returns are equally weighted. As our data are overlapping, we adjust the standard errors of the portfolio return time series using Hansen-Hodrick (1980) standard errors with the corresponding number of overlapping lags. t-statistics are reported in parentheses.

Panel A: Trades are sorted in terciles based on the distance between the investor and the firm. Investors in tercile 1 (T1) are closest to the firm and investors in tercile 3 (T3) are the farthest. Within each distance tercile, we buy the stocks in the highest tercile of retail order imbalance and short the stocks in the lowest retail order imbalance tercile. Panel A reports buy-and-hold portfolio raw returns and 4-factor alpha over 15 weeks for each distance tercile. Columns (1-2) use volume-based retail order imbalance and columns (3-4) number of trades-based retail order imbalance.

	(1)	(2)	(3)	(4)
L-S portfolio	Raw Return	Alpha	Raw Return	Alpha
T1	1.038***	1.364***	1.029***	1.189***
	(2.93)	(4.01)	(2.83)	(3.27)
T2	0. 568*	0.835***	0.660	0.766**
	(1.71)	(2.64)	(1.54)	(1.98)
T3	0.725**	0.907***	0.762**	0.816**
	(2.10)	(2.73)	(1.96)	(2.17)

Panel B: 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. Within each age group, portfolios are formed by buying stocks in the highest tercile of volume-based retail order imbalance and shorting stocks in the lowest tercile. Panel B reports buy-and-hold portfolio raw returns and four-factor alphas over a 15-week holding horizon for each age group.

L-S portfolio	Raw Return	Alpha
Group 1	0.723**	0.835**
	(2.11)	(2.45)
Group 2	1.286***	1.668***
	(3.59)	(4.80)
Group 3	0.633**	0.985***
	(2.14)	(3.57)
Group 4	0.694**	0.851**
	(2.07)	(2.54)
Group 5	0.577	0.637*
	(1.42)	(1.68)

Panel C: Retail investors are classified as sophisticated if they are based in greater Helsinki region and naïve if they are living outside the greater Helsinki area. Within each investor group, portfolios are formed by buying stocks in the highest tercile of retail order imbalance and shorting stocks in the lowest tercile. Panel C reports buy-and-hold portfolio raw returns and four-factor alphas over a 15-week holding horizon. Columns (1)–(2) use volume-based retail order imbalance, while columns (3)–(4) use trade-based retail order imbalance.

L-S portfolio	(1) Raw Return	(2) Alpha	(3) Raw Return	(4) Alpha
Helsinki	1.388***	1.718***	1.564***	1.740***
	(4.02)	(5.24)	(4.29)	(4.62)
Other	0.542	0.870**	0.593	0.665
	(1.43)	(2.45)	(1.29)	(1.57)
Helsinki - Other	0.845***	0.848***	0.972***	1.075***
	(3.77)	(3.93)	(3.25)	(4.11)

Panel D: Retail investors are classified into two groups based on gender. Within each group, portfolios are formed by buying stocks in the highest tercile of retail order imbalance and shorting stocks in the lowest tercile. Panel D reports buy-and-hold portfolio raw returns and four-factor alphas over a 15-week holding horizon. Columns (1)–(2) use volume-based retail order imbalance, while columns (3)–(4) use trade-based retail order imbalance.

L-S portfolio	(1) Raw Return	(2) Alpha	(3) Raw Return	(4) Alpha
Male	0.973**	1.430***	1.070**	1.241***
	(2.43)	(3.84)	(2.47)	(2.94)
Female	0.714*	0.916**	0.807*	0.661
	(1.92)	(2.53)	(1.71)	(1.49)
Male-Female	0.259	0.515**	0.00263	0.580**
	(1.00)	(1.98)	(0.94)	(2.08)

IA.3 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 five euros or more, the minimum tick size during the sample period is euro 0.001[14]. 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 to 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)[15]. 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.

[14] 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).

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