Retail Investors' Contrarian Behavior Around News, Attention, and the Momentum Effect*

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Abstract

Using a large panel of U.S. brokerage accounts trades and positions, we show that a large fraction of retail investors trade as contrarians after large earnings surprises, especially for loser stocks, and that such contrarian trading contributes to post earnings announcement drift (PEAD) and price momentum. Indeed, when we double-sort by momentum portfolios and retail trading flows, PEAD and momentum are only present in the top two quintiles of retail trading intensity. Finer sorts confirm the results, as do sorts by firm size and institutional ownership level. We show that the investors in our sample are representative of the universe of U.S. retail traders, and that the magnitude of the phenomena we describe indicate a quantitively substantial role of retail investors in generating price underreaction. Our findings are consistent with investors' belief in the Law of Small Numbers (LSN), or the tendency of individuals to mistakenly infer too much from small samples in their decision process (Tversky and Kahneman, 1971, Jin and Peng, 2023). Alternative hypotheses, such as the disposition effect and stale limit orders, do not explain retail contrarian trading in our sample. Younger and more attentive traders are more likely to be contrarian, and a firm's dividend yield, leverage, size, book to market, and analyst coverage are associated with the fraction of contrarian trades they face around earnings announcements. External validation tests show that our results are not confined to the specific sample of investors and time frame of our dataset.

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I. Introduction

This paper investigates the role retail investors play in the gradual incorporation of information into security prices. There is ample evidence that security prices appear to under-react to new information at short and medium horizons. For example, the stocks of companies that have announced abnormal positive (negative) earnings tend to outperform (underperform) stocks with smaller or no earnings surprises (Ball and Brown 1968, Bernard and Thomas 1989, 1990). Further, stocks with positive (negative) past recent returns tend to continue experiencing positive (negative) returns in the next nine to twelve months (Jegadeesh and Titman 1993, Chan, Jegadeesh, and Lakonishok 1996, Rouwenhorst 1998). More recent research argues that these two phenomena – earnings momentum and price momentum – are related (Chordia and Shivakumar 2006, Novy-Marx 2012, Novy-Marx 2015).

Using a dataset containing the holdings and transactions of more than 2.8 million accounts at one of the largest U.S. online discount brokers between 2010 and 2014, we document that a large fraction of retail investors trade as contrarians around news announcements, selling stocks on large positive earnings surprises, and buying stocks on negative large earnings surprises, thus possibly slowing the incorporation of information into prices and contributing to the momentum effect.

We find that the intensity of this contrarian trading is related to several factors. First, it is positively correlated with the magnitude of earnings surprises. Second, it is strongest when the investor has held the stock for more than a month, but less than a year. Third, it is related to investors' attention to the stock, as measured by whether investors log into their accounts to check news on the stocks they hold, which we can observe for a random subsample of eleven thousand accounts.

We also find that more than 50% of the stocks in the winner and loser momentum portfolios in our sample have large positive or negative earnings surprises, consistent with the results in Chan, Jagadeesh and Lakonishok (1996). This suggests that contrarian retail trading activity around large earnings surprises may play a substantial role in generating momentum and slow price adjustment to new information.

Consistent with our hypothesis that retail trading behavior around earnings announcements may lead prices to adjust slowly to new information, when we double-sort stocks based on retail trading intensity and past returns we find that the price momentum phenomenon is concentrated in the top two quintiles of retail trading activity, while it is non-existent elsewhere.

As for earnings momentum, we find that the magnitude of net retail inflows predicts the magnitude of the post earnings drift (PEAD), particularly for the stocks experiencing the largest earnings surprises (positive or negative). Tying together earnings and price momentum, we find that this effect is even stronger for stocks in the extreme momentum portfolios, particularly the momentum loser portfolios, for small stocks – consistent with the findings in Hong, Lim, and Stein (2000) – and for stocks with low institutional ownership.

These findings are not specific to our sample. We are able to bring external validity to them by replicating our main results for the general population of retail investors for the period 2010-2021 using the algorithm in Boehmer et. al. (2021) [BJZZ] to identify retail-initiated market buy and sell orders. Although recent research has raised questions about the accuracy of this algorithm in quantifying trades (Barber et. al., 2023), there is evidence that it is effective for ranking stocks based on retail trading activity (Laarits and Sammon, 2023), which is what matters for our identification strategy.

Next, we aim to understand the mechanism behind our empirical results, specifically the drivers of retail contrarian trading behavior in response to news and how that behavior is related to price and earnings momentum. Many theories have been put forth to explain stock-price momentum, some which are based on beliefs and some which are based on preferences (see e.g., Grinblatt and Han, 2005, Li and Yang, 2013, and Barberis, Jin, Wang, 2021). Within the literature on beliefs-based momentum, there are papers which argue it is generated by overreaction to news (see e.g., Hong and Stein 1999, Barberis and Shleifer 2003), while other papers argue it is due to underreaction (see e.g., Barberis, Shleifer, and Vishny 1998).

Our paper contributes to this debate by providing evidence consistent with momentum being generated by underreaction to earnings news resulting from retail investors' contrarian trading behavior. Within this family of explanations, there are two leading belief-based hypotheses which can generate such contrarian trading behavior.

One potential explanation is investors' belief in the Law of Small Numbers (LSN), or the tendency of individuals to mistakenly infer too much from small samples in their decision process

(Tversky and Kahneman, 1971). An example of this mistaken belief is the so-called “gamblers’ fallacy” by which many people expect that, after a series of coin tosses where one side of the coin has appeared more than the other, the other side of the coin is more likely to be drawn in the next toss up, even though these are all independent draws (see e.g., Rapoport and Budescu, 1992, 1997). Another example of the Law of Small Numbers is the so-called “hot hand” phenomenon, where people believe that a basketball player who has made several shots in a row is more likely to make their next shot (Gilovich, Vallone, and Tversky, 1985; Camerer, 1989; Tversky and Gilovich, 1989a,1989b).

In our setting, investors suffering from “gamblers’ fallacy” bias are more likely to believe that after a large positive earnings announcement and the subsequent positive reaction to it, earnings are likely to mean revert and prices will adjust downwards in the future, while investors suffering from “hot hands” bias are likely to believe that a positive earnings announcement is likely to be followed more positive earnings surprises and further price appreciation.

Jin and Peng (2023) develop a formal model of this hypothesis and explore its implications for investors’ behavior and price reaction. They show that LSN investors with strong beliefs in mean reversion will show contrarian trading behavior proportional to the strength of their beliefs, which in turn results in price underreaction if they constitute a sufficiently large fraction of the investor population. LSN investors with more diffused priors or even “hot hand” beliefs show a much weaker contrarian trading behavior – or even momentum trading behavior – which can result in less under-reaction and possibly over-reaction of prices.

A second, and not necessarily mutually exclusive explanation for our results, is conservatism bias where individuals are slow to update their prior views in light of new information. In our setting, investors suffering from conservatism bias, who have a strong prior that other investors overreact to news, are likely to trade contrarian and contribute to price under-reaction. A related explanation for underreaction is sticky beliefs, where investors only change their beliefs a fraction of the way toward Bayesian rational updating (Bouchaud et. al., 2019).

While both hypotheses fit our findings on price and earnings momentum, only the LSN hypothesis can also fit simultaneously our findings that investors exhibit contrarian trading behavior in stocks and the findings in Kogan et al. (2023) that investors simultaneously exhibit momentum trading behavior in cryptocurrencies. It is plausible that investors have strong priors about stocks, and more diffuse priors about cryptocurrencies given that cryptocurrencies are a relatively new asset with extremely volatile returns.

We would like to acknowledge that there are also other explanations for why prices might underreact to earnings information. Past work has shown, for example, that inattention may lead to underreaction, especially around earnings announcements (DellaVigna and Pollet, 2009, Hirshleifer et. al., 2009). We show, however, that our results are stronger in the set of investors who are paying attention – as measured by time spent doing stock research – suggesting inattention is not an explanation for observed underreaction in our data. Therefore, our preferred mechanism is a mistaken belief in the Law of Small Numbers.

We also confirm the presence of the disposition effect in our sample i.e., the tendency of investors to sell winners and hold on to losers (Shefrin and Statman, 1985, Odean 1998), and the presence of limit orders based on stale prices. We show, however, that the individuals who trade around earnings surprises tend to buy the stocks they hold after negative earnings surprises, which appears to be inconsistent with some of the theories of investor behavior that generate the disposition effect (e.g., realization utility, as discussed in Barberis and Xiong, 2012). By contrast, in the model of Jin and Peng (2023), a mistaken belief in the Law of Small Numbers can also lead investors to trade in a way consistent with the observed disposition effect.

Literature Review

Our results speak to a broad literature on the behavior of retail investors – and the associated implications for asset pricing phenomena. Our findings on individual contrarian trading behavior are consistent with Kaniel at al. (2012) who analyze the daily buy and sell volume of executed retail orders for a large cross-section of NYSE stocks in the 2000-2003 period and find evidence of informed trading by retail investors as a group. They also show that individuals in the aggregate tend to trade in the opposite direction of earnings surprises. An advantage of our setting, compared to Kaniel et al. (2012), is that we can follow each retail investor over time, rather than as a group only, and thus investigate the identity, timing, and returns of trades before and after the earnings surprises. In addition, information on the pattern of web clicks and the time spent investigating each stock and visiting different pages on the brokerage firm site allows to explore the motivations and mechanisms behind retail trading around news.

Grinblatt and Keloharju (2000, 2001) also find evidence of contrarian trading behavior by Finnish investors as a function of past returns, although in a shorter sample, and using a more indirect methodology.

By contrast, Kogan et al. (2023) find that while investors in their dataset of retail traders on the e-Toro platform trade contrarian in stocks and gold, they follow a momentum trading strategy in cryptocurrencies. In fact, through the use of account-level fixed effects, they show that the same investors exhibit the contrarian and momentum trading behavior simultaneously, depending on the asset class.

Consistent with the findings of studies of brokerage investor behavior based on a similar but older dataset covering the 1987-1992 period (Odean 1999, Barber and Odean 2000, and others), the investors in our sample trade very infrequently and hold on average a small number of stocks, although as a whole they hold the universe of publicly traded stocks. Infrequent trading makes news-based contrarian trading behavior even more significant. Moreover, it implies that, while individual investors might leave money on the table with their contrarian trading behavior, they tend to survive as a group. It also suggests that they have fewer opportunities to learn that their behavior is suboptimal, as each investor individually tends to experience only very few instances of significant earnings surprises and does not observe other investors' behavior.

The remainder of the paper is organized as follows. Section II describes the data and some summary statistics. Section III explores retail investors behavior around earnings announcements and the Momentum effect. Section IV investigates the impact of retail trading on the PEAD and Momentum. Section V extends this analysis to investigate if there is any evidence of a longer-term impact of retail trading around company news on stock returns. Section VI conducts robustness checks and explores alternative explanations to our main findings. Section VII explores the characteristics of contrarian investors. Section VIII investigates the role of attention on investor behavior. Section IX explores the strength of the contrarian selling conditional on the length of time the investor has held the stock and section X explore the characteristics of the stock portfolios in the individual accounts included in our dataset. Section XI provides external validation of our results. Finally, Section XII concludes.

II. Data, Variable Construction, and Summary Statistics

Retail Investor Data

The source of our retail investor data is a proprietary dataset from one of the largest discount brokers in the United States. This dataset contains the quarterly holdings and daily transactions and distributions (such as dividends) of more than 2.8 million accounts for the period 2010.Q1-2014.Q2. The number of accounts fluctuates over time as some accounts are closed and others are opened. There are approximately 1.560 million accounts at the beginning of the sample period, and 1.660 million at the end, with about 1 million accounts present in the data for the entire sample period. For a subset of approximately 11 thousand accounts we also have data on their online activity (logins, page views, etc.). This subset of accounts has also been studied by Gargano and Rossi (2018).

Table 1 provides summary statistics for all the accounts and securities included in the dataset. In our main analysis we restrict attention to the subset of individual accounts and, within those, the accounts which have at least one buy or sell order in securities we can match to the CRSP stock database. Table 1 shows that this captures most of the accounts and assets in the dataset.

Panel A in Table 1 shows there are 2.834 million accounts, of which 1.659 million (58.5% of the total) are individual taxable accounts, 882 thousand (31.1%) are individual retirement accounts, 267 thousand (9.4%) are institutional accounts,[1] and 27 thousand are owned by foreigners. The value of the assets in the accounts is $273 billion. Account holdings are heavily skewed to the right: The median value of holdings in individual taxable accounts is relatively small at $7.4 thousand, but the average is $81.5 thousand; for individual retirement accounts, the median value and average value are $24.1 thousand and $79.3 thousand, respectively. Not surprisingly, institutional accounts are larger on average, at $243 thousand.

Panel B in Table 1 shows the distribution of holdings in the accounts by type of security at the end of the sample period, June 30, 2014. Individual stocks constitute the dominant form of security in all accounts, at $246.6 billion (90.3% of assets), followed by much smaller holdings of mutual funds ($18.3 billion, 6.7%), bonds ($7.5 billion, 2.8%), and options and warrants ($2.5 billion, 0.9%). Individual stocks also include ETFs. The average number of stocks held in each type of

[1] They include not-for-profit organizations, corporations, partnerships, and unincorporated institutions.

account is 6, with the exception of institutional accounts at 8 stocks. The average amount of all other types of securities is very small.

Panel C shows summary statistics of account trading over the entire sample period. The median number of months with at least one trade is about 20% of the total number of months a given account is in the sample. The average number is about 30% of the total. The spread between median and average is much larger for turnover. The median monthly turnover is 6.4%, but the average turnover is much larger at 44.3%. Individual accounts, whether taxable or retirement, exhibit median turnover similar to the total sample, while institutional accounts exhibit somewhat lower median turnover at 4.8%. The large spread between the median and the mean reflects that the 20% most active accounts account for 90% of total trading, and that about 30% of the accounts are either closed or become dormant in our sample period. The median size of a trade is $3,859 and the average size is $9,825, both fairly large relative to the median and average size of the accounts.

Figure A1 in the Appendix complements the information in Panel C by showing the time series dimension of trading in our dataset. It plots the time series of rolling 60-day aggregate net purchases of stocks in the CRSP database for each type of account over our sample period (Panel A) and the cumulative net purchases (Panel B). We compute aggregate net stock purchases for each type of account in a given date by taking the difference between dollar amounts of purchases and sales for each stock by all accounts in that category, then aggregating across stocks. Therefore, this measure reflects net trading of each type of account with the rest of the market.

The upper panel in the figure shows that net purchases of stocks by each type of account exhibit significant time variability. However, the lower panel shows that on balance the investors in our data set have been exiting individual stocks over time: Cumulative net purchases are strongly negative for all types of accounts over our sample period. The experience of this very large broker suggests that retail investors have been strongly decreasing their holdings of individual stocks over this sample period. This in turn implies institutional and professional investors represent an increasing fraction of stock trading. To the extent that retail investors contribute to momentum, their exit from stock trading points to a declining relevance of momentum in the years to come.

Table 2 shows summary statistics of the demographics of account holders. The dataset contains only sparse demographic information to protect the privacy of account holders. We observe the gender, age, and 5-digit zip code of account holders. Panel A of Table 2 shows that account holders are predominantly male (64.5%), but there is still a large proportion of females (25.4%).[2] The age distribution is bell shaped, and peaks at 43 years old. Figure A2 in the Appendix shows that older individuals tend to have larger accounts and hold less of their account balances in individual stocks, and more in bonds and mutual funds. Panel B of Table 2 shows that account holders are located all over the United States except for a few counties in the Midwest and Western states, and that the larger accounts tend to be concentrated in urban areas and both coasts.

Company data: Asset Prices, Returns, Financials, and News

The dataset from the discount broker contains for each security the name of the security, contemporaneous CUSIP number, ticker symbol, description of the type of security and, for bonds, options, and warrants, the terms of the security.

To construct a complete picture of each account asset holdings, we link investors' holdings and transactions data across various financial datasets by constructing a comprehensive security master table for different asset classes. We use the security identification information to extract price and return data for each security from multiple data sources: CRSP, FactSet, Bloomberg, TRACE, Municipal Securities Rulemaking Board (MSRB) and OptionMetrics.

We use this merged dataset to calculate NAV and total return of each individual account. For accounts with external flows, we take timing of deposits and withdrawals into account and calculate the time-weighted return.

As previously noted, our analysis restricts attention to stocks in the individual accounts for which we find a match in the CRSP database. This includes holdings of individual stocks, equity mutual funds, and ETFs. We exclude OTC "penny" stocks from our analysis. The investors in our sample hold hundreds of them, but their aggregate dollar value is minuscule.

To select the securities included in our analysis, we get a unique list of CUSIP-date observations from all the trades in our dataset, and then seek to match each CUSIP-date pair to a

[2] About 10% of the accounts do not have gender information.

NCUSIP-date pair in CRSP, where NCUSIP is the historical CUSIP in the CRSP MSENAMES database. If that fails, we match based on CUSIP.

Earnings Surprises Measure

To study earnings surprises, we further restrict our security sample to those stocks that are in I/B/E/S. Most publicly traded stocks have analyst coverage. If anything, this sample selection criterion likely biases results against our findings, as small loser stocks with low analyst coverage are more likely to display momentum and tend to be held by retail investors (Hong, Lim, and Stein, 2000).

Following standard practice in the literature (e.g. Hartzmark and Shue, 2018), we measure earnings surprises (SUE) as realized earnings per share relative to mean consensus analyst forecasts and scale this difference by the stock price the day before the announcement. This offers a cleaner measure of the magnitude of the surprise, since the price on the day of the announcement will already incorporate the impact of the surprise. Replacing price with other scaling factors such as consensus earnings forecasts or measures of dispersion of analyst forecasts does not alter the conclusions of our empirical analysis.

We use COMPUSTAT and I/B/E/S to extract financial information and analyst earnings expectations about the companies in the dataset. To link the same security across multiple datasets, we use the unique identifier of the issuing company.

III. Retail Investor Trading Around Earnings Surprises and the Momentum Effect

Our analysis of individual investors' contrarianism focuses on the behavior of investors around earnings announcements. In our view, earnings surprises provide an excellent laboratory to explore contrarianism in investor behavior for four reasons. First, unlike most other types of company news or economy-wide news, the sign of the impact of earnings surprises on stock prices is unambiguous, particularly for large surprises. Second, earnings announcements are arguably one of the most important pieces of news companies release about their performance and their financial health. Third, companies release information about their earnings with relatively high frequency: Earnings announcements, together with company presentations, are the single most frequent type of company news. Fourth, we have good measures of earnings expectations from market participants.

Earnings Surprises and the Momentum Effect

We start by providing in **Figure 1** a visual representation of the link between earnings surprises and price momentum for the sample of stocks included in our analysis.

Panel A in the figure plots the fraction of firms in each momentum portfolio that have at least one earnings announcement with an absolute value of SUE greater than 0.5 standard deviations over the momentum portfolio formation period. Panel B plots the fraction of earnings announcements with an absolute value of SUE greater than 0.5 standard deviations over the same period for the firms in each momentum portfolio.[3]

Figure 1 suggests that sorting stocks on past returns is not independent of sorting stocks on past earnings surprises, consistent with the results in Chordia and Shivakumar (2006) and Novy-Marx (2015). On average the winner and loser portfolios tend to comprise a larger number of firms that experience large earnings surprises, and a larger number of large surprises. Panel A shows that firms with large earnings surprises represent about 50% of the stocks in those portfolios, while for the other portfolios they represent at most 40%. Similarly, Panel B shows that large earnings surprises constitute a much larger fraction of total earnings surprises in the extreme momentum portfolios than in the other momentum portfolios.

Momentum and Retail Flows around Earnings Surprises

In **Figure 2**, we explore the relation between momentum and retail net inflows into stocks. Panel A plots the time series average of the demeaned daily net retail flow for each momentum portfolio in our sample. We compute net flow for each stock-day pair in our dataset as the difference between buy and sell orders on the stock as a fraction of its total trading volume that day, as

[3] The results are robust of setting the threshold to 1 standard deviation or higher.

recorded in CRSP. We demean it by subtracting the cross-sectional average across all stocks in our sample each day. Finally, we take the average of the demeaned net flows across all days in the momentum holding period month (i.e. month 0). Following the literature, we demean net inflows to normalize our measure for the market-wide flows on that day.[4]

Panel A shows that retail investors behave as contrarians on past returns: on average they buy negative momentum stocks and sell positive momentum stocks. The relation between net retail inflow and price momentum is monotonic across the momentum portfolios. Panel B plots the time series average of daily absolute retail flows into momentum portfolios, computed for each stock-day pair as the sum of buy and sell orders as a fraction of total trading volume. This panel shows that the absolute flow is larger for the extreme momentum portfolios, particularly for the loser portfolio. The vertical axis in the plot shows that the purchases and sales of the retail investors included in our sample account for about 3.5% of market volume in the stocks in the "loser" portfolio, and about 2.5% of market volume in the "winner" portfolio.

To build the momentum portfolios we follow Ken French's methodology and apply the following screens: Each month during the period June 2010 to June 2014 we sort stocks into 5 groups based on their cumulative return in months t-12 through t-2, excluding stocks with more than four missing returns in the last 12 months, and with missing or stale prices in month t-12. We focus only on the price of ordinary common shares traded on major exchanges. Although the portfolios include NYSE, AMEX and NASDAQ stocks, the portfolios are constructed using NYSE prior (2-12) return quintile breakpoints. Momentum portfolio 5 corresponds to the equal-weighted portfolio of stocks in the top quintile of cumulative returns during the formation period, and momentum portfolio 1 corresponds to those in the bottom quintile of cumulative returns. We refer to them as the winners and losers portfolios, respectively.

Although the **magnitudes** in Figure 1 and Figure 2 might seem modest, they are in fact very significant once we take into account that, although our sample is highly representative of the overall population of retail investors, it still constitutes a small fraction of such population. Total stock holdings in our sample as of June 2014 were $264 billion, compared to the $13,883 billion in assets owned by all households according to the Flow of Funds data from the Federal Reserve.

[4] Kaniel et al. (2008) normalize their retail flow measure by the historical average flow but specify that their results are robust to using the normalization above.

Accordingly, our sample represents about 1.77% of retail holdings. To the extent that the trading of our investors is representative of the trading of the overall household sector, the modest inflows relative to total trading volume need to be scaled up significantly. An alternative and independent back of the envelope calculation, based on estimating retail holdings as (1 – ownership by 13F-filing institutions) for each stock, suggests that the investors in our sample to account for about 2% of total retail holdings on a value-weighted basis and 4% of on an equal-weighted basis, implying a scaling factor between 25 and 50 times. Additionally, **Figure 3** shows that our investors account for about 3% of total trading volume on an equal-weighted basis (1.3% on a value-weighted basis) during our sample period (July 2010 through June 2014).

Figure 4 shows that retail contrarian trading is strongest in stocks with the largest absolute SUEs over the previous 12 months. Each panel in this figure reproduces Panel A in Figure 2 by grouping stocks with earnings announcements into terciles according to the absolute magnitude of their earnings surprises in the momentum holding period month. The figure shows that net inflows into the extreme momentum portfolios appear to be more significant for those stocks experiencing the largest earnings surprises, both positive and negative. The losers portfolio experiences positive net inflows, while the portfolio of winners experiences negative net inflows. The middle tercile shows a similar contrarian pattern, although less pronounced, and the lowest tercile doesn't show a pattern.

Further, **Figure 5** shows that if we separate stocks into 5 groups based on the intensity of retail trading over the whole sample period, we find that momentum is only present in the two groups with the highest retail trading intensity, and more so in the group with the highest intensity, consistent with our hypothesis that retail investors contribute to price underreaction through their contrarian trading behavior.

Each panel in this figure plots the average return during the portfolio formation month of the five momentum portfolios when we split the stocks in them according to the intensity of retail trading, measured as gross retail flows. Specifically, each month during the period June 2010 to June 2014 we sort stocks into 5 groups based on their cumulative return in months t-12 through t-2. Then, within each group, we form 5 sub-groups based on average gross retail flow into each stock over our whole sample period, and compute the return to each of the resulting 25 portfolios during month t. We then take the time series average of the portfolio returns. The panels in Figure 5 are vertically ordered from least retail trading intensity (top panel) to most retail trading intensity (bottom panel). Gross (or absolute) flow is defined as the average of buy and sell volume for each stock-month pair, normalized by total volume in CRSP. The spread between losers and winners' returns is as large as 2.8% per month in the top quintile of retail trading intensity. Moreover, there is a roughly monotonic pattern of increasing returns from the bottom to the top momentum portfolio in those two quintiles. By contrast, there is no return spread across momentum portfolios for the stocks in the three quintiles with the lowest intensity of retail trading (top three panels in the figure).

Daily Evidence

To further investigate the link between retail trading, surprises, and momentum, we zoom in on the daily retail flows around the announcements.

Panel A of **Figure 6** plots the average cumulative demeaned net inflow into stocks divided into 5 groups based on their signed earnings surprises (SUE) each quarter for a window of 60 trading days centered around the announcement (30 days before and 30 days after). The panel shows that retail investors consistently buy stocks with negative earnings surprises and sell stocks with positive earnings surprises. On announcement day there is a positive net inflow into stocks for all SUE-based portfolios, consistent with Frazzini et al (2006) and Hirshleifer et al (2008). However, the portfolios in the top four quintiles of earnings surprises experience a quick and sharp reversal in net inflows right after the announcement day and exhibit negative net inflows over the subsequent 30 trading days. The portfolio of the stocks with the lowest SUE continues to experience positive net inflows over the subsequent 30 trading days.

Panel B in Figure 6 further separates the retail flow by momentum and by sign and magnitude of the earning surprise. The figure reports the results for the stocks in the extreme momentum portfolios while the complete figure is available upon request. The left side of this figure shows that stocks with low past returns tend to experience inflows as shown in Figure 2. These inflows are strongest for the firms that end up having the lowest earnings surprises. The right side of the figures shows that also analogously to Figure 2, stocks with the largest past returns tend to experience outflows. Those outflows tend to be more pronounced for firms with the highest earnings surprises, but the spread across SUE groups is smaller than for the momentum losers.

IV. Post Earnings Announcement Drift, Momentum, and Retail Investor Flows

In **Figure 7** we examine the relation between the contrarian pattern of retail investors net flows into stocks around earnings announcements, past returns, and the post-earnings announcement drift (PEAD) of Bernard and Thomas (1989, 1990). The left panel of the figure plots the cumulative gross return on the stocks with the lowest past returns in months t-12 to t-2 (momentum portfolio 1) and the lowest (most negative) earnings surprises (SUE portfolio 1) in a 44-trading day window centered around earnings announcements. It shows that the PEAD of this group of stocks becomes increasingly more negative as retail buying pressure increases. The PEAD is most pronounced for the group with the most positive net flow. Similarly, the right panel focuses on the stocks with the largest past returns (momentum portfolio 5) and highest earnings surprises (SUE portfolio 5) and shows that in this group of stocks the PEAD is the most positive for the stocks with the biggest retail net outflow.

The magnitudes are quantified in the tables below the figures. Among the losers experiencing bad surprises, the PEAD monotonically increases with the strength of retail flows. This is true for the announcement day return, ranging from -2.02% for the lowest quintile of retail flow, to -7.01% for the highest quintile, as well as the post drift return (days +1 to 22 after the announcement), which ranges from +0.26% for the lowest quintile of retail flow, to -5.5% for the highest quintile. The results are weaker for winners, including those experiencing large positive surprises. The announcement day return is higher for winner experiencing retail investors outflows, quintile 1 of the retail flows. Such return is 3.26%, compared to 2.75% for the winners experiencing retail investors inflows, quintile 5 of the retail flows. Moreover, the returns from day 1 to 22 are close to zero and mostly positive.

PEAD by Market Capitalization and Institutional Ownership

Figure 8 explores the relationship between PEAD and retail trading intensity when we group stocks by market capitalization. We define large and small capitalization stocks as stocks with 1-month lagged market capitalization larger or smaller than the median capitalization among NYSE firms, respectively.

Panel A in Figure 8 shows cumulative gross returns on small and large capitalization stocks in a 44-trading day window around earnings announcements when we group firms in five portfolios according to the size of their earnings surprises. This panel shows that small stocks, for which retail investors as a group exhibit relative preference, experience both larger jumps in prices and stronger PEAD than large capitalization stocks, particularly those with the lowest (i.e., most negative) earnings surprises. Panel A also shows that large capitalization stocks do not appear to exhibit PEAD.

However, this panel hides PEAD patterns that surface when we further subset stocks by the intensity of retail trading, as measured by retail net inflows. Panel B in the figure shows that for small capitalization stocks, the negative PEAD is much stronger for stocks with the largest positive net inflows (retail group 5) and the worst earnings surprises. A negative but less pronounced PEAD appears for large capitalization stocks with the largest positive net inflows (retail group 5).

In **Figure 9** we group stocks by institutional ownership, defined as the fraction of shares outstanding held by 13F-filing institutions. Low (high) institutional ownership is defined as institutional ownership lower (larger) than the median. Panel A shows that PEAD is strongest among stocks with low institutional ownership, consistent with institutions being more likely to follow momentum strategies. This effect is stronger for stocks that experience the most negative earnings surprises, and among such stocks, for stocks that experience the largest net retail inflow (retail group 5) (Panel B).

V. Retail Trading and Long-Term Returns in Momentum Portfolios

The empirical evidence on price momentum suggests that it can persist for a few months beyond the portfolio period formation. Thus, it is natural to explore if there is any evidence of a longer-term impact of retail investors trading around company news on stock returns.

Figure 10 suggests that over a longer horizon the timing and direction of the retail flows lines up with the peaks and throughs of the cumulative returns of the short legs for the group of stocks experiencing the worst earning surprise. For each panel, the top left graph plots the cumulative retail net inflow into momentum portfolios. Portfolio 1 corresponds to the bottom quintile of stocks, i.e. those with the lowest returns in months 2-12 prior to portfolio formation, and portfolio

5 to the top quintile of stocks with the highest returns. The remaining graphs show the cumulative return for the short (Med – Lo) and long (Hi – Med) legs, and the Hi-Lo portfolio, respectively. Panel A shows the results for the worst quintile of earnings surprises, while Panel B shows the results for the best one.

Figure 11 plots cumulative returns on momentum portfolios in the 12 months following portfolio formation, as a function of the magnitude and size of the earnings surprise at month t and of the intensity of the retail trading activity. The left panel plots the 12-month cumulative returns on the five momentum portfolios for the stocks with the most negative surprises. Each plot in the panel plots returns on these stocks when we further divide them by intensity of retail trading. The right panel is similar, except that it focuses on the socks with the most positive earnings surprises.

The left panel shows that among the stocks with the worst earnings surprises, those experiencing the largest positive net inflows (retail group 5) tend to exhibit the most negative returns over the following 12 months. The right panel shows a symmetrical effect for momentum stocks experiencing the most positive earnings surprises and the largest outflows (retail group 1). Such stocks exhibit the most positive returns in the post-formation period, particularly the stocks in the winner portfolio.

Overall, the evidence shown in Figure 10 and Figure 11 suggests that the impact of retail contrarian investor behavior on stock prices goes well beyond a few days around company news announcements and might extend to months beyond the announcements.

VI. Robustness Checks and Alternative Explanations

The Disposition Effect

A possible alternative explanation for the net selling of stocks with positive earnings surprises is the disposition effect, the tendency of investors to prioritize assets with embedded capital gains over those with capital losses when selling a stock (Shefrin and Statman, 1985; Odean, 1998). The disposition effect is a widely studied and widespread phenomenon.

In order to distinguish this explanation from contrarianism we proceed in two steps. First, we show that the investors in our sample do indeed suffer from the disposition effect, and then we zero in on their trading around earnings surprises and show that the disposition effect doesn't explain investor behavior in this setting.

Table 3 reports the estimated disposition effect in our sample of retail investors using a methodology similar to Odean (1998). *Pct. Loss (Gain) Realized, PL(G)R*, is calculated as the number of stock positions that were sold at a loss (gain) divided by total number of stock positions that had losses (gains), both realized and on paper. A negative difference between PLR and PGR suggests investors are more likely to realize a gain than a loss, i.e. the disposition effect. The table reproduces the results in the Odean (1998) study for ease of comparison and shows that the investors in our sample exhibit the disposition effect, and, if anything, the magnitude of the effect appears to be larger in our sample than in Odean's (1998) sample.

Table 4 contains the analysis of the trading behavior of the same investors around earnings announcements. The analysis is performed on a 1% sample of the accounts. For each positive earnings surprise, we collect the portfolios of all investors in the sample who hold that stock. We then perform regressions with investor-surprise fixed effects, i.e. for each investor-surprise, we check which of the stocks in her portfolio, if any, the investor traded in the days around the surprise, from day -1 to +3, and specifically whether it was a stock with a gain (disposition effect) or the one with a surprise regardless of the embedded capital gains (contrarianism), or one with both.[5]

The disposition effect predicts that stocks for which the investor has a gain are more likely to be sold, i.e. a positive sign on the *Gain* coefficient.[6] Column (1) of the table shows that around earnings surprises having a gain on a stock is unrelated to the likelihood such stock will be sold. The coefficient is both economically and statistically insignificant.

Colum (2) shows that a stock experiencing a positive earnings surprise is 1.16 percentage points more likely to be sold, compared to a baseline probability of 8.92% of selling a different stock in the investor portfolio at that time. Column (3) reports the results of a regression with controls for both the presence of a capital gain, a positive surprise, and their interaction. It confirms the results of the previous two columns: around earnings surprises investors act as contrarian and

[5] Separating day -1 from days 0 to 3 doesn't affect the results (available upon request).
[6] To calculate the gain, we use the average cost basis method, whereby we assume the cost of buying the shares of the stock being sold is equal to the average cost of that stock's shares in the investor portfolio.

don’t seem to display the disposition effect. The interaction terms also indicates that conditional on a positive surprise, having a gain doesn’t increase the probability the stock is sold.

Column (4) and (5) split the sample into investors who have bought the surprise stock within the [-1,+3] interval and those who have been holding the surprise stock before day -1, respectively. The results indicate that contrarianism is concentrated among those who buy the stock around the surprise episode. For these investors, the coefficient of the interaction term is negative and statistically significant, indicating that, conditional on a positive earnings surprise, the presence of an embedded gain makes the probability of selling the stock in the short period after the announcement slightly lower.

Finally, Column (6) controls for the fact that earnings surprises tend to be clustered in time and that it is possible that the investor sells a different stock than the surprise stock we are looking at, but that such stock is also experiencing a surprise in those days. Indeed, the coefficient on the dummy variable capturing whether the investor sells other stocks in her portfolio that also have a positive surprise in that time interval is positive and statistically significant, reinforcing the result that investors are more likely to sell a stock with a positive surprise. Similar to the results in Columns (3)-(5), whether these other stocks are also experiencing a capital gain is not an economically nor statistically significant determinant of the probability of selling.

Stale Limit Orders

Another potential explanation for our findings is that the contrarianism we observe is a mechanical result of stale limit orders posted by retail investors some time before the earnings surprise, and possibly forgotten, and that are eventually fulfilled by following the jump in price generated by the earnings announcement.

Figure 12 shows that this is not a concern in our dataset: 34.3% are limit orders placed by our investors are filled when they are placed, and an additional 46% are filled within 36 seconds from the time they are placed. These statistics are even starker if we weight the orders by dollar amount, in which case we find that the additional 46% of orders that is not executed immediately is fulfilled within 6 seconds.

Rebalancing and Tax Considerations

In future work we plan to also investigate portfolio rebalancing and tax considerations as possible explanations of our results. These explanations are unlikely to account for the phenomena we observe as they have been already dispelled by Odean (1998) as not being major drivers of retail investor trading.

VII. Who is Contrarian?

Individual Contrarian Score

While contrarian trading behavior by retail investors around earnings announcements is statistically and economically significant, not all retail investors are contrarians. **Figure 13** plots the distribution across individuals of the fraction of their earnings-related trades that are contrarian. The left panel includes all individuals who execute at least 2 earnings-related trades, while the right panel restricts the sample to those who execute at least 12 earnings-related trades during their time in the sample. We define a trade as contrarian if it is a buy (sell) between t and t+3, and the SUE was less (greater) than zero.

Both panels show that there is dispersion in the buying and selling behavior of individual investors around earnings surprises with respect to contrarianism. Although contrarian trading appears more often in our sample than trend trading, the latter is still significant. The right panel shows that for the population of investors who trade often around earnings announcements, more than 50% of them trade contrarian at least half of time, and more than 65% trade contrarian at least 40% of the time. But close to 50% of investors trade non-contrarian at least half the time. Nevertheless, only 10% always trend-trade. This proportion goes to 20% in the population that trades less frequently on earnings announcements.

We find that contrarian scores are higher for younger investors and those who make round trips trades around the earnings announcement. By contrast, once we control for the variables above, gender doesn't appear to be statistically significantly related to the share of contrarian trades an investor makes around earnings announcements.

Firm Contrarian Score

Similarly, in **Figure 14** we report the distribution of the fraction of trades that are contrarians for each earnings announcement. Such fraction is zero for earnings surprises where none of the investors in our sample who traded did so in a contrarian manner, while it is equal to one for the announcements where all those who traded were contrarians.

The graph shows that about 12% of the earnings announcements do not have any contrarian trades among the investors in our sample, while about 3% only have contrarian trades. The distribution of the remaining scores appears to be symmetric around 50%.

In **Table 5** we investigate the characteristics of the firms with more contrarian trades around their earnings announcements. We focus on sale transactions in Columns (1) to (4), and on buy transactions in Columns (5) to (8).

As a baseline, in Columns (1) and (5) we regress the fraction of contrarian trades in each earnings announcement on year dummies. The coefficients show that the average fraction of contrarian trades by announcement is stable over our sample for both buys and sales.

In Columns (2) and (6) we control for market beta, dividend yield, t-12 to t-2 returns, and liquidity, as measured by Kyle's (1985) lambda. We find that stocks with higher betas, lower dividend yields, and lower past returns tend to experience a higher fraction of contrarian sales around their earnings announcements. A one-point increase in the stock's beta is associated with a 2.5 percentage point increase in the fraction of contrarian trades, while a one percentage point increase in the dividend yield or in the past returns is associated with a 3.11% and a 2.71% decrease in such fraction, respectively. By contrast, the stocks that experience more contrarian buying around negative earnings surprises tend to have higher dividends and lower past returns. The effect is particularly strong in the case of dividends: a one percentage point higher dividend yield is associated with a more than twice as big fraction of contrarian buys. A one percentage point lower past return is associated with a 2.04 percentage point higher fraction of contrarian buys. The association between market beta and the fraction of contrarian buys is both economically and statistically insignificant. Finally, liquidity doesn't appear to be statistically significantly related to neither contrarian buys nor sales.

When we further control for firm size, as measured by assets, book to market ratio, gross profitability, leverage, number of analysts covering the stock, institutional ownership, and market capitalization, we find that the coefficients on the original controls are stable and that among the new control variables only book to market, leverage, and analyst coverage matter for the sales (Column (3)). Specifically, a 0.10 increase in the book-to-market (leverage) ratio is associated with a 2.10 (0.50) percentage points increase in the fraction of contrarian sales following a positive earnings surprise. An additional analyst following the stock is associated with 13.4 basis points increase in such fraction. For buys, among the additional control variables firm size, gross profitability, the number of analysts, institutional ownership, and market capitalization are statistically significant. Column (7) shows that a $10 million increase in firm size is associated with a 3.8 percentage points increase in the average fraction of contrarian buys. A one percentage point increase in gross profitability is associated with a 4.29 percentage points drop in it, while an additional analyst with a 24.2 basis points increase in such fraction. A one percentage point increase in institutional ownership is associated with 7.24 percentage lower contrarian buys share. Finally, in Columns (4) and (8) we re-run the same regressions controlling for year fixed effects and obtain qualitatively and quantitatively similar results.

VIII. The Role of Attention

In this section we investigate the role of attention on investor behavior. For a subset of our sample of retail investors, we can observe how active they are in the trading platform, i.e. how often they log into their online account, and how often they look up a stock in the research page of their online account.

Table 6 examines buying and selling behavior conditional on earnings announcements for this sub-sample of 11 thousand investors. We construct an indicator variable that takes a value of 1 if the investor has been looking up a stock in the research page of her online account prior to the earnings announcement.

Columns (1) and (4) of Table 6 confirm that our investors tend to sell stocks with positive earnings announcement returns and buys stocks with negative earnings announcement returns. We calculate earnings announcement returns as the cumulative return on the stock in the five trading days following the earnings announcement. A one percentage point increase in the earnings return is associated with a 92 basis points higher probability of selling the stock. Compared to the same table for a large sub-sample not conditional on the availability of clicks information (Table 1A in the Appendix), the coefficients are larger, indicating that this contrarian behavior is, if anything, more intense for this subsample of individuals.

Column (2) and (5) show that the coefficient on the attention variable is positive and statistically significant in both selling and buying, consistent with the positive relationship between trading and attention. Column (2) shows that, holding earnings returns constant, the probability of selling for an investor who has researched the stock on the platform is 1.9 percentage points higher than for one who hasn't. However, conditional on doing research a higher earnings return doesn't further increase the probability of selling in a statistically significant way. By contrast, Columns (4) to (6) show that paying attention amplifies the increase in the probability of selling associated to lower earnings returns. A one percentage point lower earnings return is associated with a 67.6 basis point higher probability of selling for an investor who didn't do any research on the platform, compared with a 1.72 percentage point higher probability for one who did.

Attentiveness might be positively correlated with self-perceptions of expertise and beliefs in market overreaction to news.

Finally, we note that our results are a lower bound on the effect of investor attention as we only observe investor logins and engagement on the trading platform and cannot control for sources of information outside the platform that our investor possibly access.

IX. Holding Periods

Table 7 explores the strength of the contrarian selling conditional on the length of time the investor has held the stock. It presents regressions of selling behavior on the earnings announcement return and the earnings announcement return interacted with a dummy variable indicating the number of months during which the investor has accumulated the stock. For stocks held at the inception of the sample, we assume the stock was purchased on that date.

The results in Table 7 show that contrarian selling behavior is pervasive across holding horizons, except for stocks acquired in the same month the earnings announcement takes place. Contrarian trading is strongest at shorter holding horizons and weakens for stocks held for longer horizons.

X. Factor Tilts

In this section we explore the characteristics of the stock portfolios in the individual accounts included in our sample, and their evolution over the sample period. This provides a benchmark of the representativeness of our sample of the population of individual investors with brokerage accounts and a comparison with the prior literature which has explored similar datasets (Barber and Odean, 2013, Betermier, Calvet, and Sodini, 2017, and Campbell, Ramadorai, and Ranish, 2014, among others). We also build a novel analysis of stock characteristics of individual investors' portfolios using the methodology of Daniel, Grinblatt, Titman, and Wermers (1997). Given the focus of our main analysis, we emphasize the results regarding momentum factor exposures in this section.

We build daily portfolio holdings and end-of-day balances for each individual account using the initial snapshot of portfolio balances in our dataset, daily transactions, and our matched pricing data, after adjusting shares for splits and distributions. These constructed balances are highly consistent with the actual end-of-quarter snapshot holdings provided in the dataset, particularly for equities.

We explore the characteristics of investors' portfolios by running regressions of monthly returns at the account level onto the returns of Fama-French portfolios including Market, Size, Value, and Momentum. **Table 8** reports the distribution of the coefficients. Panel A reports the distribution of the estimated coefficients, and Panel B the distribution of the coefficients with p-values below 10% under the null hypothesis of zero coefficients (except for the market factor, which is one). We include accounts with at least 12 months of return history and balances above

$1,000 during the account history. We exclude coefficient estimates in the bottom 1% and upper 1% of the distribution.

Table 8 shows that the average account has an exposure to the market factor close to one (0.95). However, among the accounts with market betas significantly different from one (about 25% of them, or 591 thousand accounts), the average market factor exposure is significantly lower, at 0.80. The average account exhibits a tilt toward small stocks and growth stocks, and away from momentum stocks. These tilts are even more pronounced for accounts with statistically non-zero factor exposures.

The table also shows that there is also considerable cross-sectional variation in factor exposures across accounts. At least 25% of the accounts exhibit tilts in the opposite direction of the average account, towards high beta stocks, toward large stocks, and toward value stocks. Interestingly, the negative exposure to momentum appears to be pervasive across the sample, particularly in the subset of accounts with significant exposure to the momentum factor: at least 75% of the accounts with significant exposure to momentum exhibit a negative exposure. Moreover, when we group accounts by the size of their balances and by their trading activity, all groups within each dimension exhibit a negative exposure to momentum (see Table A1 in the Appendix). The magnitude of the negative exposure to momentum is strongly negatively correlated with account size, and positively correlated with trading activity.

Finally, Table 8 shows that the estimated intercept or "alpha" in individual factor regressions is not statistically different from zero for all 2.4 million accounts except for 270 thousand of them. But for these accounts, alpha is overwhelmingly negative: The average non-zero alpha is highly negative at -1.2% per month, and the 75th percentile of the distribution still exhibits a negative alpha of -0.2%. Only the top 10% of the accounts with non-zero alphas exhibit a positive alpha. In sum, the vast majority of investors in our sample do not exhibit positive excess returns once we control for their portfolio exposures to the market, size, value, and momentum factors. If anything, they experience significantly negative factor-adjusted returns.

Our estimates of factor exposures and alpha are consistent with estimates for other groups of investors reported in the literature: U.S. brokerage accounts in the early 1990's (Barber and Odean, 2013), Swedish investors (Betermier, Calvet, and Sodini, 2017), and Indian retail investors (Campbell, Ramadorai, and Ranish, 2014).

We also analyze the characteristics of these investors' portfolios using stock characteristics in addition to factor portfolios. This approach allows us to examine the time series variation of factor tilts in the portfolios. We construct stock characteristics for size, value, and momentum using the methodology of Daniel, Grinblatt, Titman, and Wermers (1997), DGTW henceforth. For each month and for each characteristic we divide stocks in five quintiles and assign a score to the stocks in each group. For example, a stock with a DGTW score of 5 in each characteristic is a stock that falls in the top quintile by size, book-to-market, or positive momentum. Next, we divide accounts in four groups as a function of their median balances over account history and treat each group as a single account or portfolio. Accounts in group 4 are those in the top quartile of the distribution of that month balances. Given this grouping, we compute the average characteristic of each portfolio as the value-weighted average of the scores of each of the stocks in the portfolio.

Figure 15 plots the monthly time series of the characteristics of each account size group. The size characteristic of each group appears to be very stable over time. Consistent with our factor regressions, larger accounts tend to have a more pronounced tilt toward large stocks than smaller accounts. Value exhibits more time variation, but there is still a stable ordering of the characteristic across account sizes, with larger accounts tilting more toward growth stocks than smaller accounts.

In contrast, the momentum characteristic of each group exhibits very significant variation over time. This time series variability in the momentum characteristic could be the result of investors purposely changing their exposure to momentum (i.e., the result of factor timing), the result of trading activity they do for reasons other than factor timing, or the result of changes in the characteristics of the stocks they hold. **Figure 16** shows results consistent with the third possibility. This figure shows that the accounts with the lowest trading activity within each size group still exhibit portfolio characteristics similar to the general population of accounts. Because trading is almost absent in these accounts, changes in the characteristics of the portfolios in these accounts must be the result of changes in the characteristics of the stock they hold. Size appears to be stable characteristic of a stock over time, at least through the four-year span of our sample period, but value and very especially momentum vary over time. Among the three characteristics we consider, momentum is the stock characteristic with the most time series variability.

These results suggest that retail investors do not engage in factor timing. This doesn't mean that investors do not have a preference for certain characteristics when they buy a stock. But some characteristics are more easily observable than others to unsophisticated investors because they are more visible and stable over time. Size is an example of a visible, stable characteristic. Momentum, however, it is not as easily observable. It requires paying attention to the stock and perhaps other stocks to notice the empirical regularity, or to investigate academic research in factor timing. But even if investors went through that analysis, they would also learn that exploiting momentum requires relatively frequent trading. Therefore, it is not plausible to think that investors exhibit an explicit preference for momentum stocks when they buy a stock, and that they would then not trade on the characteristic.

XI. External Validation of Results

One concern with our results is that they are specific to the sample of retail investors in our dataset. It could be, for example, that investors who select into the brokerage we study are especially contrarian, even though we have shown that they seem representative of the broader retail investor population in several dimensions. A second concern, which applies to any sample of investors with a limited temporal dimension, is that our sample period is one in which this contrarian behavior might have been more prevalent among retail investors.

To allay these concerns, we replicate three of our main our results using the algorithm in Boehmer et. al. (2021) [BJZZ henceforth] to quantify aggregate retail activity. Specifically, following BJZZ, we use sub-penny price improvements in the TAQ data to identify retail-initiated market buy and retail-initiated market sell orders for each ordinary common share traded on major exchanges that can be mapped map between TAQ and CRSP for the period 2010 and 2021. We exclude data before 2010 is excluded owing to the classification failures discussed in BJZZ. [7]

We define gross retail trading activity as the sum of retail buys plus retail sells divided by total trading volume. That is, gross retail activity is the share of total trading volume coming from marketable retail orders identified by the BJZZ algorithm. We define net retail trading activity as retail buys minus retail sells, again divided by total trading volume.

[7] Recent research (see e.g., Barber et. al., 2023) has raised questions about the usefulness of the BJZZ algorithm for precisely quantifying retail trading volume. However, Laarits and Sammon (2023) provide evidence that the BJZZ algorithm is effective for ranking stocks based on retail trading intensity. Further, we obtain a similar ranking of stocks based on retail trading intensity using the improved algorithm proposed by Barber et. al., (2023) for identifying retail-initiated trades.

The first result we want to confirm using this aggregate retail activity data is that price momentum is strongest in high retail trading intensity stocks. **Figure 16** reproduces Figure 5, for this data.[8] The top panel of Figure 16 shows the results for stocks with the lowest gross retail activity (P1) while the bottom panel shows the results for stocks with the highest gross retail activity (P5). Consistent with Figure 5, we find that the difference between returns in the winner and loser portfolio is strongest among high retail stocks.

The second result we wish to confirm using the BJZZ data is that the post-earnings announcement drift (PEAD) is strongest in high retail stocks. To this end, we sort firms into 5 portfolios each month based on gross retail trading activity. Then, we examine earnings announcements in the following month, and form 5 portfolios based on standardized unexpected earnings (SUE). The left panel of **Figure 17** shows the cumulative returns from t-22 to t+22 around earnings announcements for stocks with the lowest gross retail activity over the prior month. The right panel shows the same quantity for stocks with the highest gross retail activity over the prior month. Consistent with the results in Figure 9, the PEAD is stronger – especially after positive news – in stocks with high past retail intensity than in stocks with low retail intensity.

We also wish to confirm our results in Figure 7 that the PEAD is the strongest in stocks where retail investors are more contrarian after the earnings announcement itself. To this end in **Figure 18** we sort firms into 5 groups each quarter based on their SUE. Then, within each of these quintiles, we sort firms into 5 sub-quintiles based on net retail trading activity from t=0 to t=22 i.e., after the earnings announcement. Net retail trading will be positive when retail investors (as a group) are net buyers, while it will be negative when they are net sellers.

Figure 18 shows the results for stocks in the bottom quintile of SUE (left panel) and the top quintile of SUE (right panel). The left panel shows that the PEAD is strongest after bad news when retail are net buyers – as evidenced by the purple line drifting down significantly after the announcement, relative to the top 3 groups of net retail activity. Similarly, the right panel shows a large PEAD when retail are net sellers after good news (blue and red lines). But here the evidence is more mixed, as there is also a strong PEAD when retail investors are net buyers (purple line). One potential explanation for the differential results for negative and positive surprises is

[8] Similar to Figure 5, we form 5 portfolios based on returns from t-12 to t-2. Then, within each of these portfolios, we form 5 sub portfolios based on gross retail activity over the same t-12 to t-2 period. Within each of these 25 portfolios, we compute average returns over the following month.

identification inaccuracies in the BJZZ algorithm. But another plausible explanation is that while retail investors can buy any stock in the investable universe, they can for the most part only sell stocks they own – due to short sale constraints.

Finally, we find most of our refinements of the above results on retail trading intensity and the PEAD also hold when using aggregate retail trading activity measured using the BJZZ algorithm. For example, in unreported results we find the effect of retail on the PEAD is stronger in small cap and low institutional ownership stocks. Together all this evidence suggests that our results are not specific to our sample of retail traders and are not specific to the specific time period in our original sample.

XII. Conclusions

This paper expands our understanding of the role of retail investors in the diffusion of information in asset markets and the determination of asset prices, specifically price underreaction to news. We examine retail investor trading behavior around company news announcements using a database containing the quarterly holdings and daily transactions of the clients of one of the largest discount brokers in the United States in the period 2010.Q1-2014.Q2.

We document that retail investors tend to trade as contrarians after large earnings surprises, both positive and negative. The retail investors in our sample also exhibit a disposition effect.

Contrarian trading behavior does not appear to be information driven on average. Investors who trade contrarian on stock news do not appear to trade in advance of the announcement. Instead, this behavior appears to be related to attention: Those who pay more attention to the stocks they hold, as measured by their online activity, trade as contrarians more intensely on news announcements.

Our results are consistent with investors' belief in the Law of Small Numbers (LSN), or the tendency of individuals to mistakenly infer too much from small samples in their decision process (Tversky and Kahneman, 1971). Jin and Peng (2023)'s LSN-based model of investor behavior shows that investors suffering from "gambler's fallacy," or the belief that shocks mean revert, are likely to behave contrarian in the presence of large shocks, particularly with strong priors and slow learning. They show that this behavior can result in price underreaction.

We hypothesize that the brokerage retail investors in our sample behave as LSN investors who believe that a large earnings surprise is likely to revert and consistent with this belief they trade contrarian. In doing so, they hold portfolios that exhibit significant negative alphas and negative exposure to the momentum factor, which is even more pronounced for those investors that trade more intensely. The small number of stocks each account holds, coupled with the relative infrequency of announcements, might prevent this population of investors from learning that their trading behavior is suboptimal.

More importantly, we provide evidence that their trading behavior might contribute to generate underreaction of stock prices to news and the momentum effect. When we double sort stocks in quintiles based on momentum and the strength of retail contrarian trading, we find that the momentum phenomenon arises only in the 4th and 5th quintile of contrarian trading intensity.

Overall, we have established that retail net inflows into individual stocks appear to be negatively correlated with price momentum and that this contrarian effect is concentrated among the stocks with the largest earnings surprises. This contrarian retail investor behavior contributes to price momentum by inducing price underreaction to news, as the momentum spread is largest for the stocks with the most intense retail trading activity, and nonexistent for stocks with low retail trading intensity. Retail net inflows around earnings announcements are contrarian, particularly for stocks experiencing the most extreme earnings surprises (and past returns). Moreover, retail net flows predict a PEAD, particularly for the stocks experiencing the largest earnings surprises (positive or negative). This effect is even stronger for stocks in the extreme momentum portfolios, for small stocks, and for stocks with low institutional ownership. But a PEAD still exists for large stocks and stocks with high institutional ownership which are more intensely traded by retail investors.

Our results suggest that the strength of momentum in asset prices should be positively correlated with the time series of the wealth-weighted importance of direct retail investor stock ownership. We plan to explore this in future research.

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Figure 1. *Fraction of Stocks and Announcements with Large Surprises by Momentum Portfolio*

Panel A shows the fraction of firms in each momentum portfolio that had one or more earnings announcements with an absolute value of SUE greater than 0.5 standard deviations. Panel B shows the fraction of earnings announcements in each momentum portfolio with an absolute value of SUE greater than 0.5 standard deviations. The momentum portfolios are computed by sorting stocks into 5 groups based on their cumulative returns between months t-12 and t-2. 5 denotes most positive momentum portfolio and 1 denotes most negative one. The standard deviation is computed on the whole sample between months t-12 and t-2. Each bar represents an equal-weighted average within each momentum portfolio.

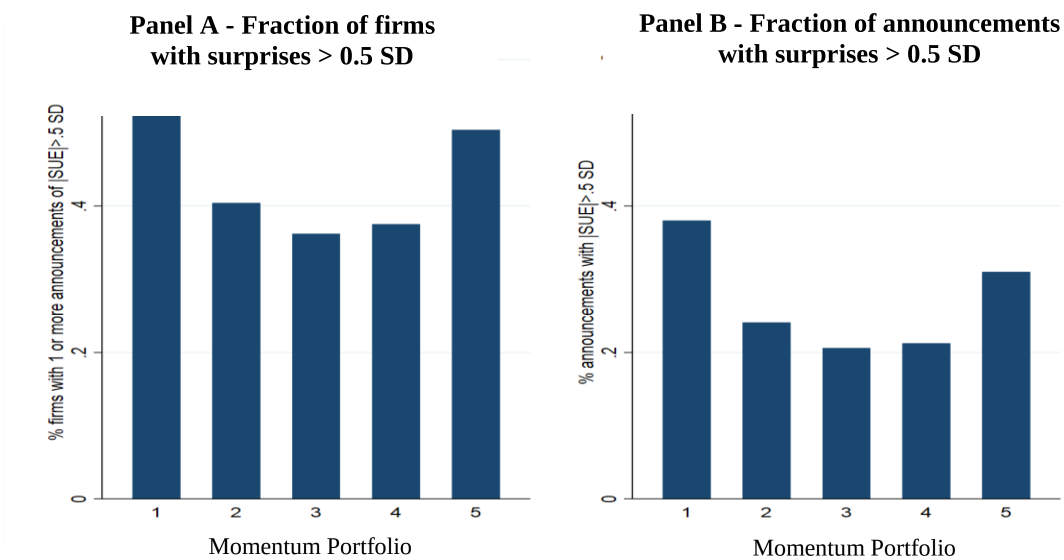


Figure 2. *Retail Inflows into Momentum Portfolios*

Panel A (B) shows the average net (absolute) retail flow into momentum portfolios, Net flow is defined for each stock-month pair as buy volume minus sell volume and it is demeaned by the average net flow in that month. Absolute flow is defined as the average of buy and sell volume for each stock-month pair. The momentum portfolios are computed by sorting stocks into 5 groups based on their cumulative returns between months t-12 and t-2. 5 denotes most positive momentum portfolio and 1 denotes most negative one.

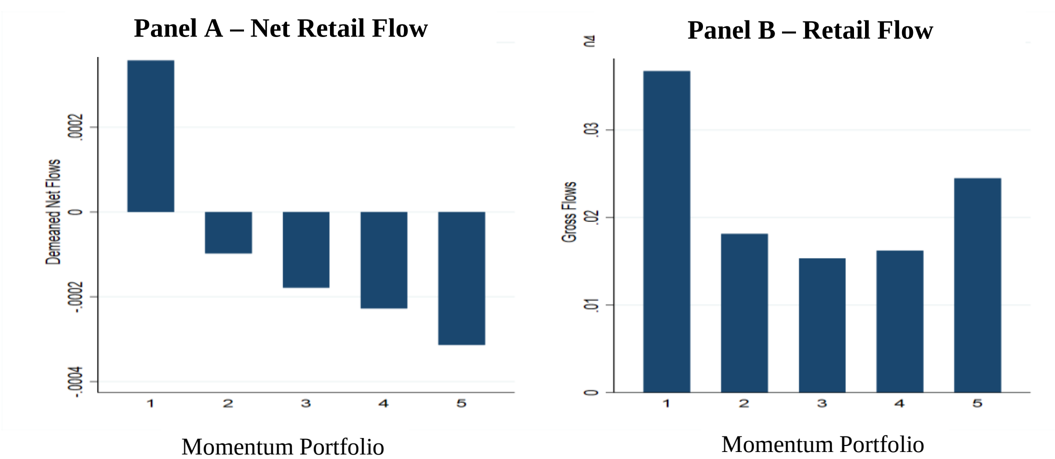


Figure 3. *Fraction of Total Volume captured by our Sample*

This graph plots the equal weighted (blue line) and value-weighted (red line) fraction of total volume the retail investors in our sample are responsible for during the time period ranging from the beginning of July 2010 to the end of June 2014. Volume is defined as the sum of buy and sells, scaled by total CRSP volume. Weights are calculated based on the market capitalization of each stock at the end of the previous month.

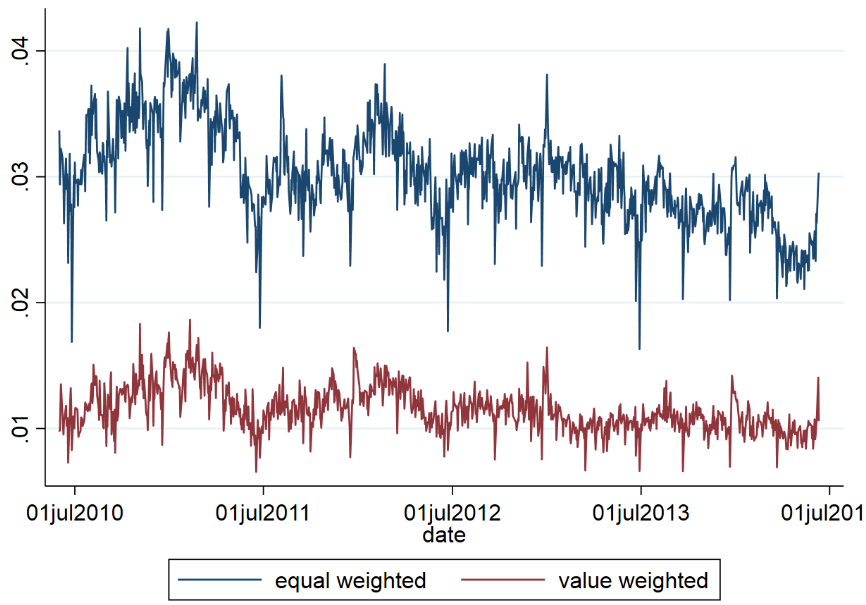
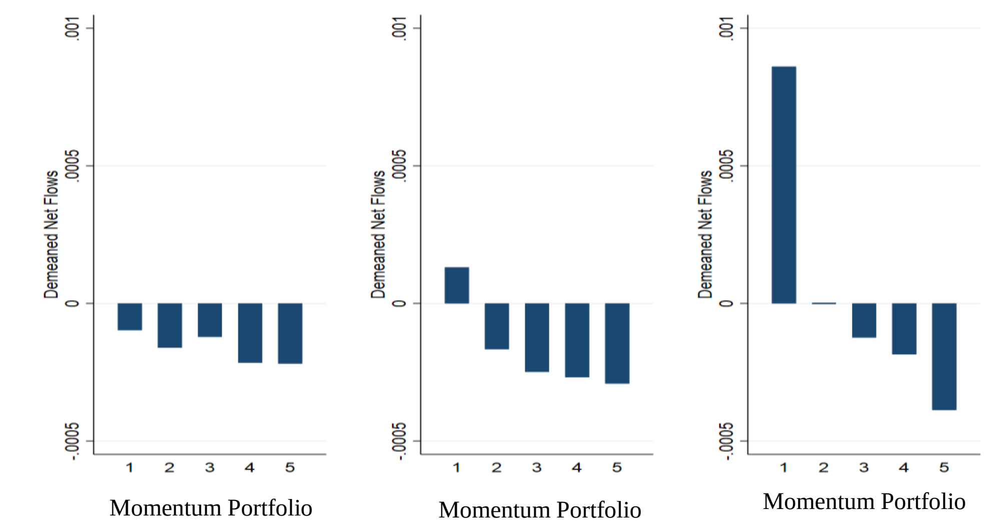


Figure 4. *Retail Net Inflow into Momentum Stocks by Size of the Earnings Surprise*

The figure plots cumulative retail net inflow into momentum stocks by absolute magnitude of earnings surprise. x-axis denotes the momentum portfolio: 5 denotes most positive momentum portfolio and 1 denotes most negative one. From left to right, the panels plot the flows for the bottom to top tercile of absolute earnings surprises. Earnings surprise (SUE) is defined as difference between actual EPS and average analyst EPS estimate divided by stock price. For each panel, we compute the average daily demeaned net retail flows for each firm each month. We then take the equal-weighted average of these demeaned net flows the month after the 5 x 3 groups are formed on past returns and absolute SUE.



Terciles of absolute earnings surprises

Figure 5. *Momentum Returns by Intensity of Retail Trading*

Each month, we sort firms into 5 groups based on their cumulative returns from t-12 to t-2 (horizontal dimension). Then, within each of these groups, we form 5 sub-groups based on average absolute retail flows into each stock over our whole sample (vertical dimension). Each bar represents the average monthly return (in %) for each of these 25 groups.

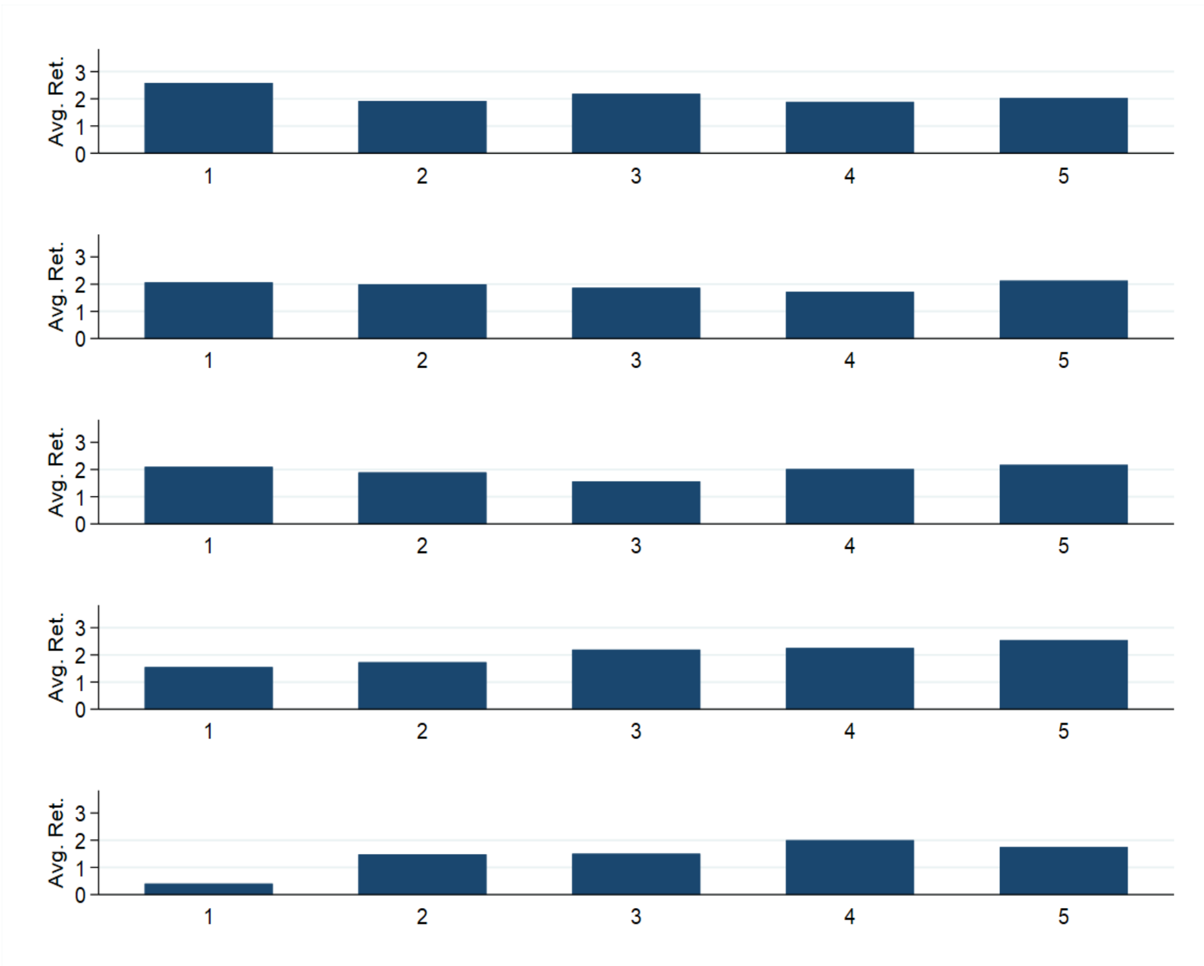
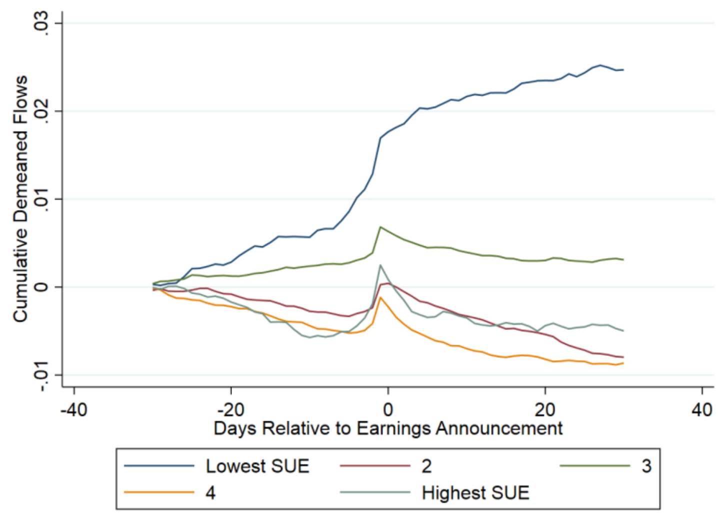


Figure 6. *Daily Net Retail Flows around Earnings Announcements*

Panel A plots the average cumulative retail net flow into stocks divided into 5 groups based on the size of their SUE each quarter. Panel B plots the average cumulative retail net flow into stocks divided into 5 momentum portfolios and then within each portfolio into 5 groups based on the size of their SUE each quarter. The left (right) graph in the panel plots the flows for the loser (winner) portfolio. Net retail flow is defined as net buy volume divided by total trading volume for a stock, and it is normalized by subtracting its sample average each quarter.

Panel A – Net Retail Flow into SUE quintiles



Panel B – Net Retail Flow into Losers and Winners and SUE groups

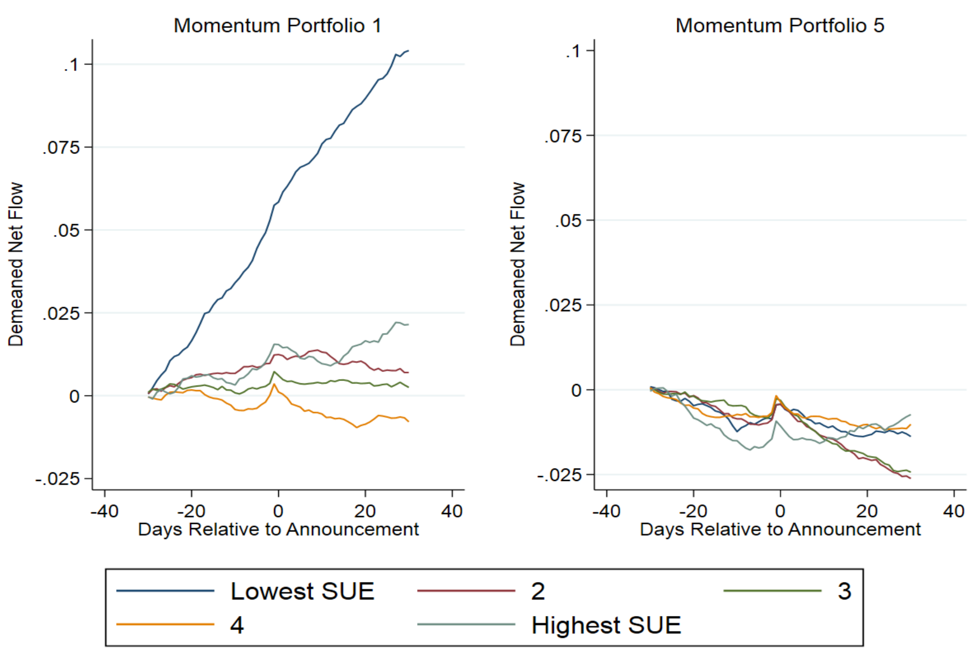
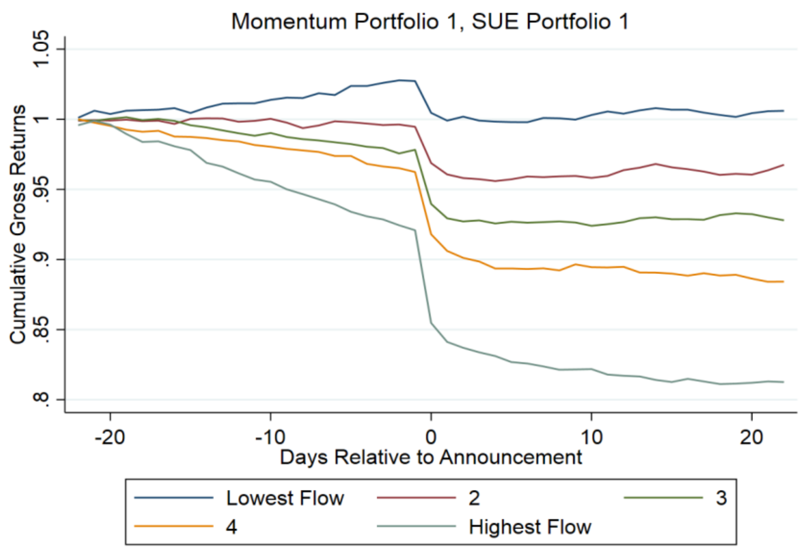
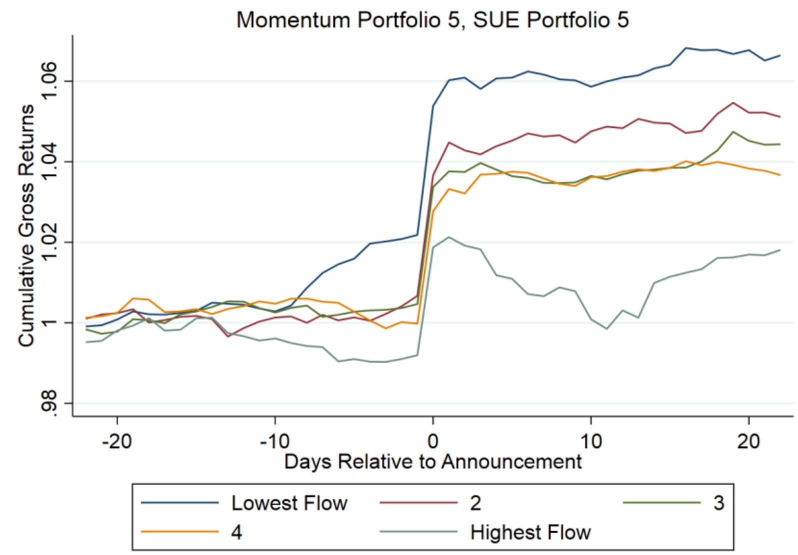


Figure 7. *Cumulative Returns by Momentum Portfolio, Size of the Earnings Surprise and Net Retail Flows*

Each month, we sort firms into 5 groups based on their cumulative returns from t-12 to t-2. Then, we sort firms into 5 subgroups based on their SUE. Then, within each of these 25 groups, we form 5 further subgroups based on the cumulative demeaned net retail flow from t=0 to t=+22. For each of these 5 x 5 x 5 = 125 groups, we calculate the average cumulative return starting at t=-22. The top panel plots the cumulative returns for firms with the lowest past returns and lowest SUE, while the bottom one plots the cumulative returns for firms with the highest past returns and highest SUE.





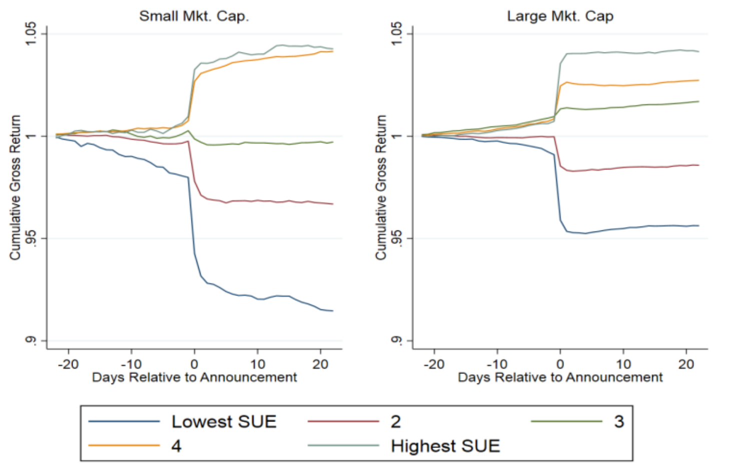
Momentum Portfolio	SUE quintile	Retail flow quintile	Cumulative return from t=0 to t==1	Cumulative return from t=1 to t==22
1	1	1	0.9798	1.0026
1	1	2	0.9749	0.9973
1	1	3	0.9613	0.9859
1	1	4	0.9555	0.9621
1	1	5	0.9299	0.9450

Momentum Portfolio	SUE quintile	Retail flow quintile	Cumulative return from t=0 to t==1	Cumulative return from t=1 to t==22
5	5	1	1.0326	1.0099
5	5	2	1.0305	1.0134
5	5	3	1.0294	1.0099
5	5	4	1.0297	1.0057
5	5	5	1.0275	0.9981

Figure 8. *Cumulative Returns by Momentum Portfolio, Size of the Earnings Surprise, Net Retail Flows and Firm Size*

Each month, we break firms into two groups based on whether their 1-month-lagged market capitalization is larger or smaller than the median among NYSE firms. Then, each quarter, we sort firms into 5 groups based on their SUE. For Panel A, within each of these groups, we calculate the average cumulative market-adjusted return starting at t= -22. For Panel B, we further sort firms into 5 sub-groups based on their cumulative net demeaned retail flows from t=0 to t=22. Within each of these 5x2x5=50 groups, we calculate the average cumulative market-adjusted return starting at t=- 22.

Panel A



Panel B

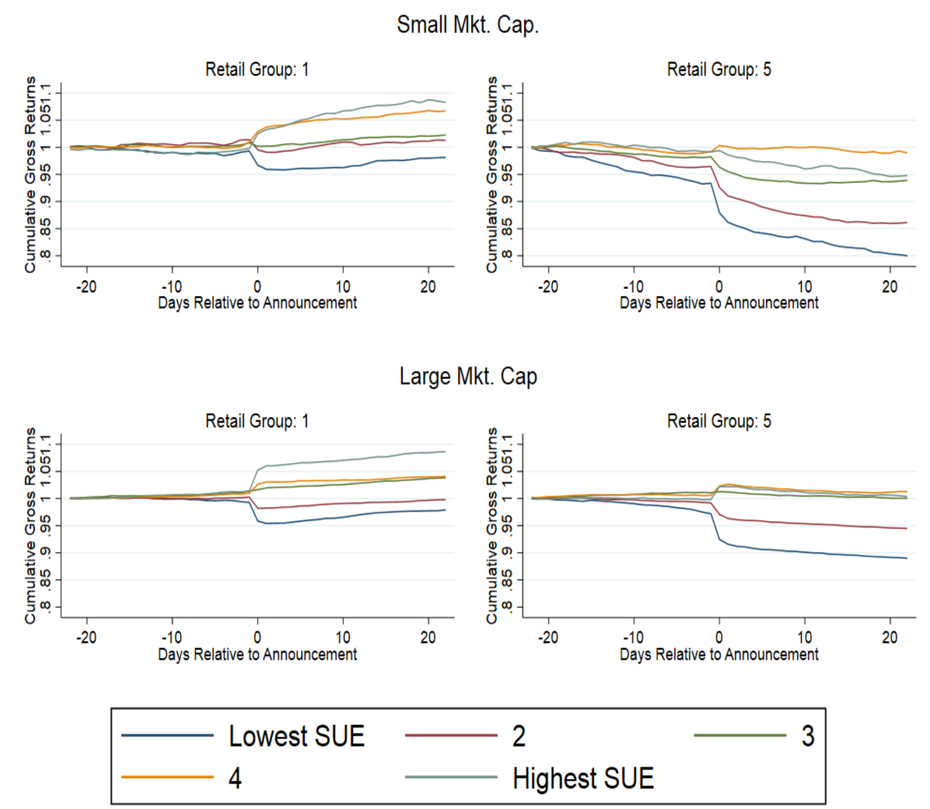
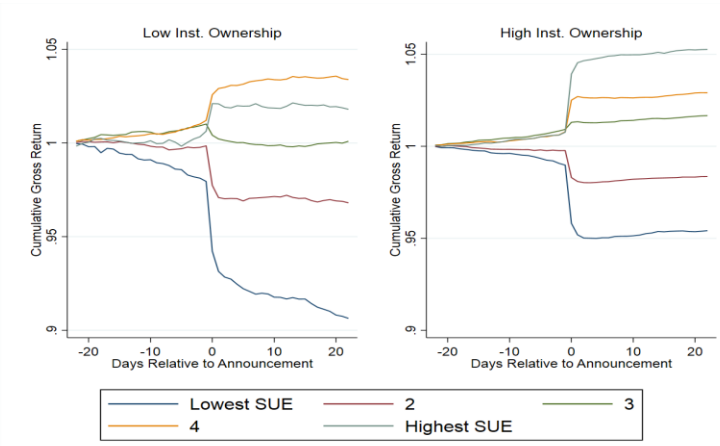


Figure 9. *Cumulative Returns by Momentum Portfolio, Size of the Earnings Surprise, Net Retail Flows and Institutional Ownership*

Each month, we break firms into two groups based on whether whether their institutional ownership – defined as the fraction of their shares outstanding held by 13-F filing institutions -- is larger or smaller than the median among NYSE firms. Then, each quarter, we sort firms into 5 groups based on their SUE. For Panel A, within each of these groups, we calculate the average cumulative market-adjusted return starting at t= -22. For Panel B, we further sort firms into 5 sub-groups based on their cumulative net demeaned retail flows from t=0 to t=22. Within each of these 5x2x5=50 groups, we calculate the average cumulative market-adjusted return starting at t=- 22.



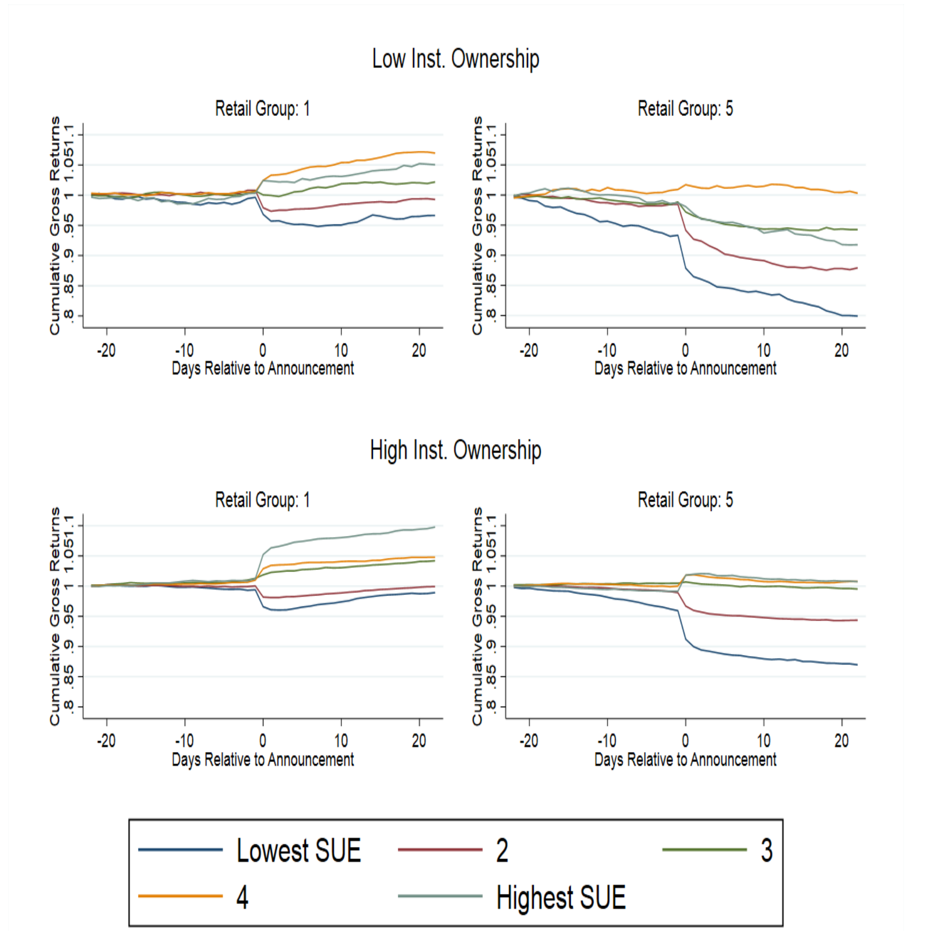
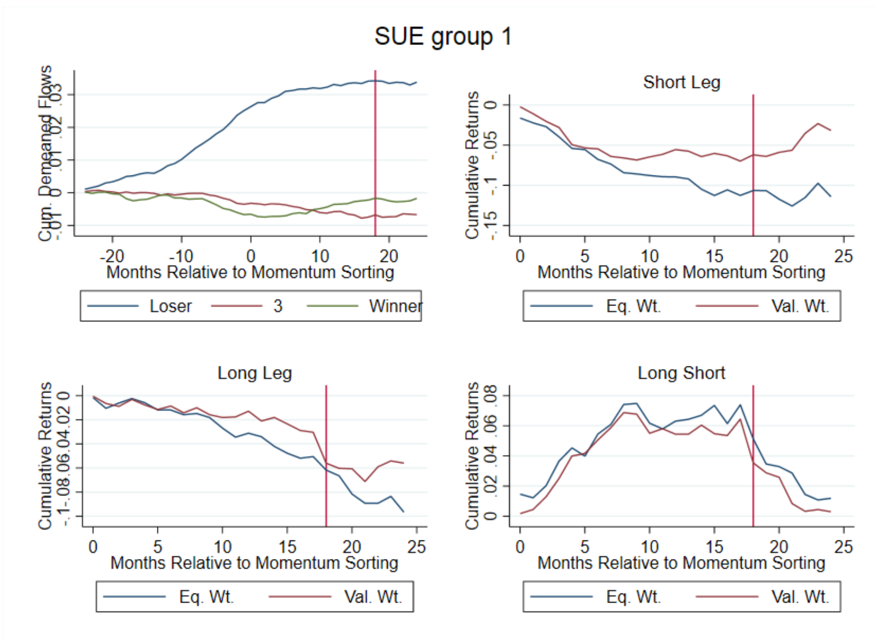


Figure 10. *Cumulative Retail Net Inflow into Momentum Stocks by SUE Group – Longer Horizon*

For each panel, the top left graph plots the cumulative retail net inflow into momentum portfolios. Retail net inflow is defined as net buy volume divided by total trading volume for a stock, and it is normalized by subtracting its sample average. Month 0 is the portfolio formation month. Portfolio 1 corresponds to the bottom quintile of stocks with the lowest returns in months 2-12 prior to portfolio formation, and portfolio 5 to the top quintile of stocks with the highest returns. The remaining graphs show the cumulative return for the short (Med – Lo) and long (Hi – Med) legs, and the Hi-Lo portfolio, respectively. Panel A shows the results for the worst quintile of earnings surprises, while Panel B shows the results for the best one.

Panel A



Panel B

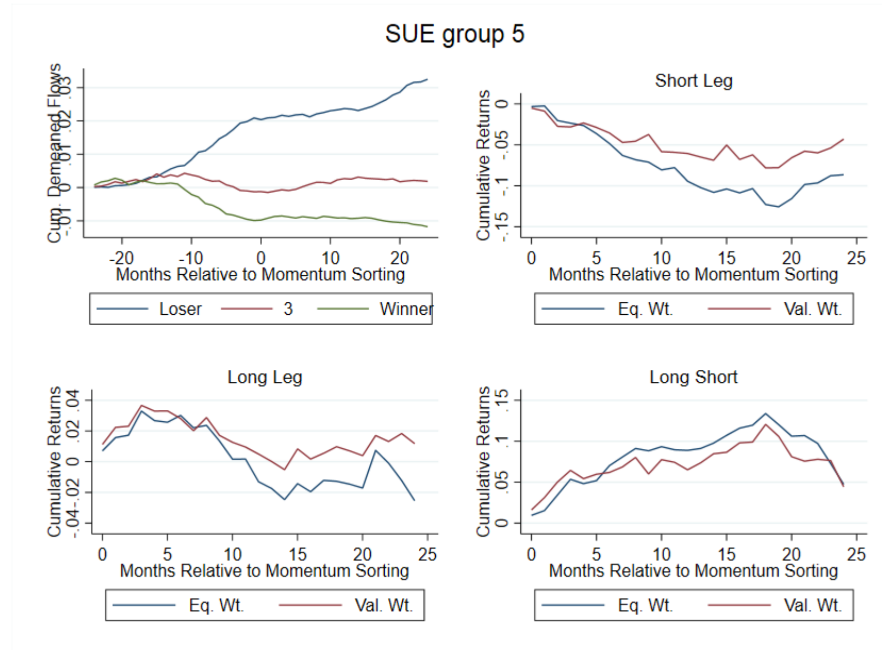
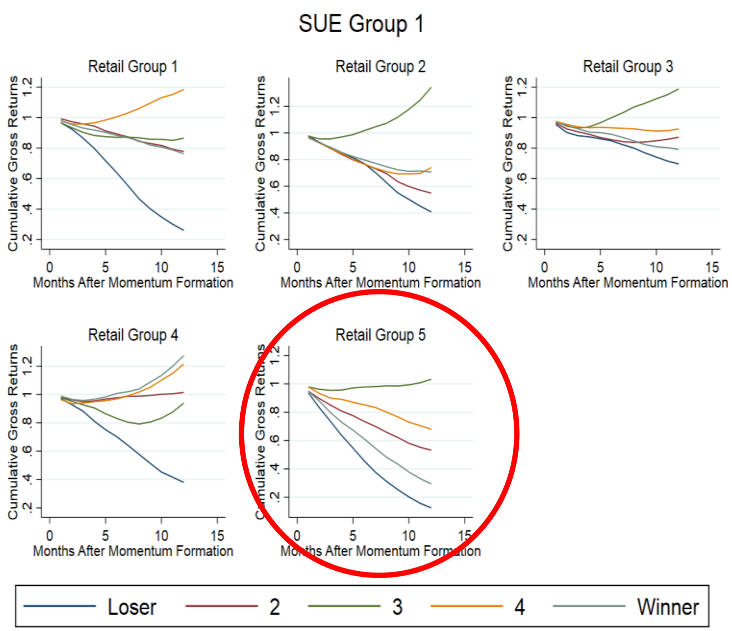


Figure 11. *Longer-run Returns by Momentum, Size of the Earnings Surprise and Net Retail Flows*

Each month, we sort firms into 5 groups based on their cumulative returns from month t-12 to t-2. Then, we form 5 sub-groups based on the SUE in the first month after forming groups on past returns. Finally, within each of these 5 x 5 = 25 groups, we form 5 further sub-groups based on average net demeaned retail flows in the month of the earnings announcement. For each of these 125 groups we compute the cumulative returns starting at month t=0 to month t=12. Panel A plots the cumulative returns for firms with the worst earnings news, while Panel B plots the cumulative returns for firms with the best earnings news.



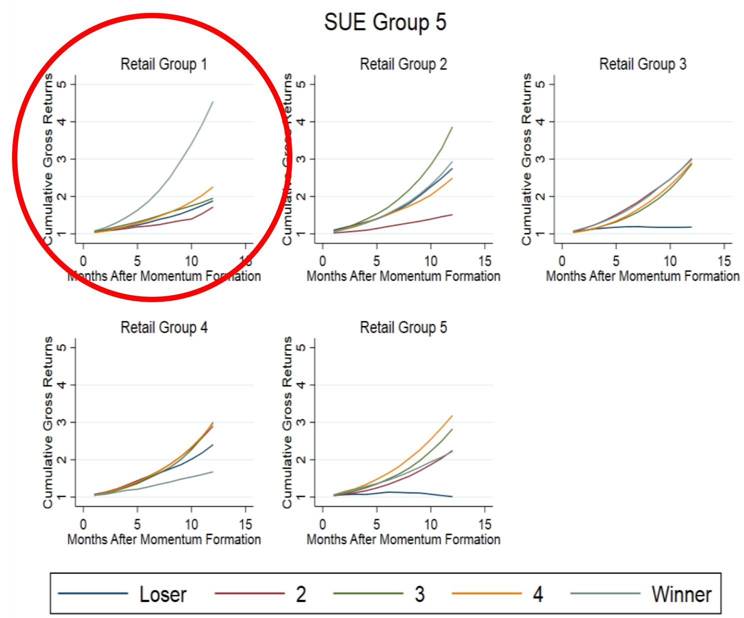


Figure 12. *Limit and Market Orders*

The figure plots the cumulative probability (left panel) and the cumulative percentage of dollar volume (right panel) against the gap between the time an order is posted and the time it is executed, measured in minutes.

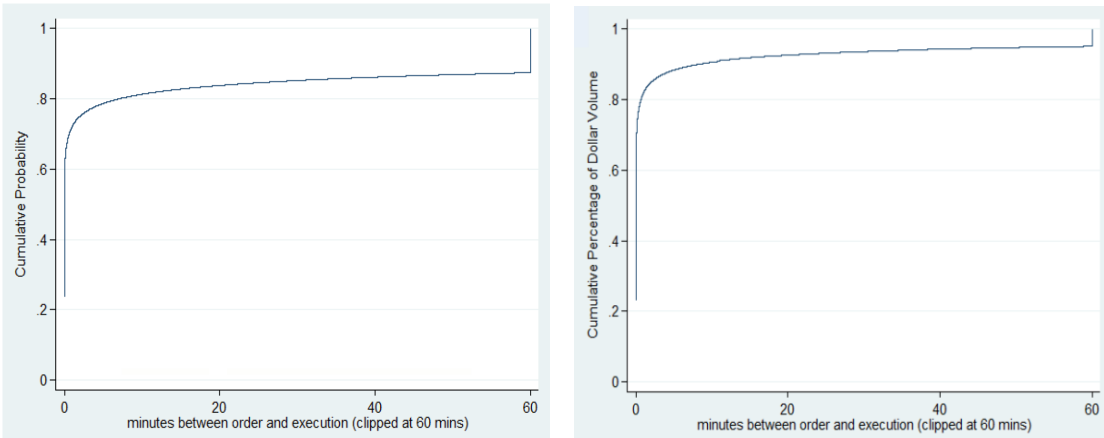


Figure 13. *Retail Contrarian Index*

The figure plots the distribution across individuals of the fraction of their earnings-related trades that are contrarians for all individuals who execute at least 2 earnings-related trades (left panel) and at least 12 earnings-related trades (right panel) during their time in the sample.

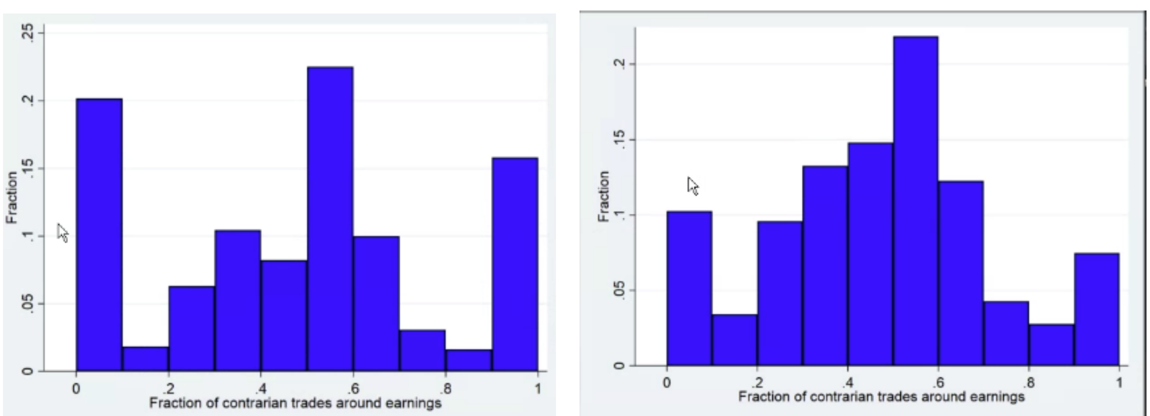


Figure 14. *Firm-level Contrarian Index*

The figure plots the distribution of the fraction of contrarian trades per earnings surprise. A trade is contrarian if the individual investor sells following a positive SUE or buys following a negative one. The measure plotted below is 0 for earnings surprises where none of those who traded among our investors traded as contrarians, while it is equal to one if they those who traded were contrarians.

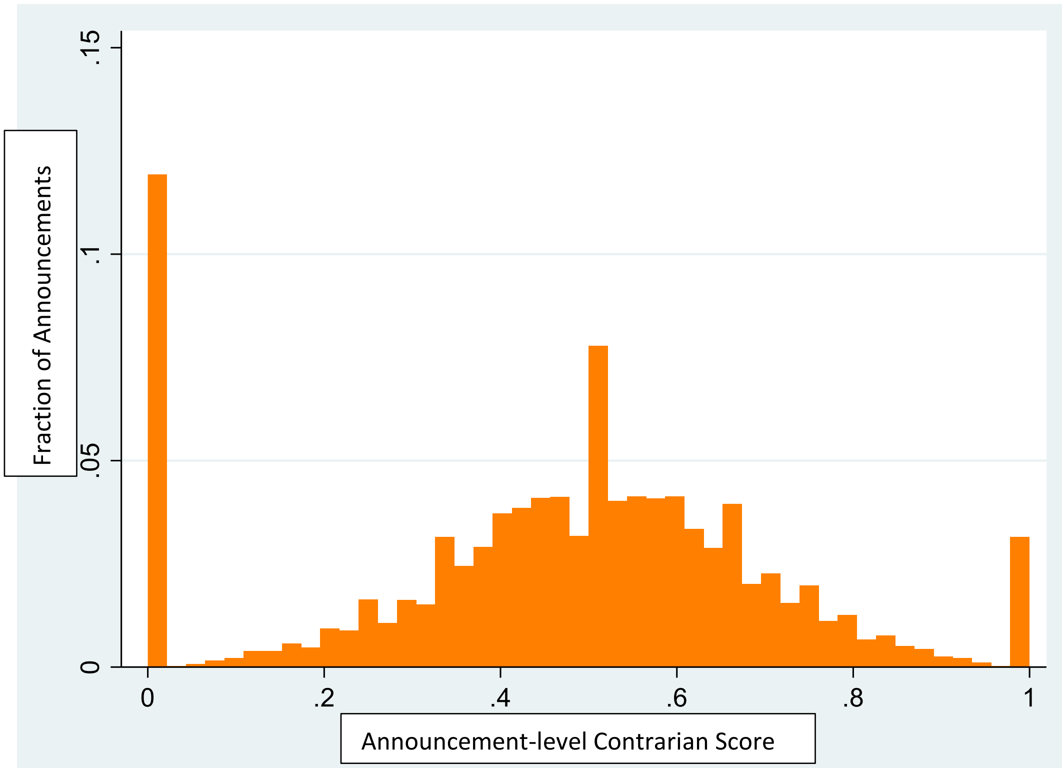


Figure 15. *DGTW Stock Characteristics: by Account Size*

This graphs below plot times series of average DGTW stock characteristics of retail stocks holdings by account size. y-axis is the index of the DGTW group a stock belongs to. Top left is size, 5 being largest stocks. Top right is valuation, 5 having highest book-to-market ratio. Bottom left is momentum, 5 having highest prior return. Bottom right is excess return after adjusting for DGTW stock characteristics.

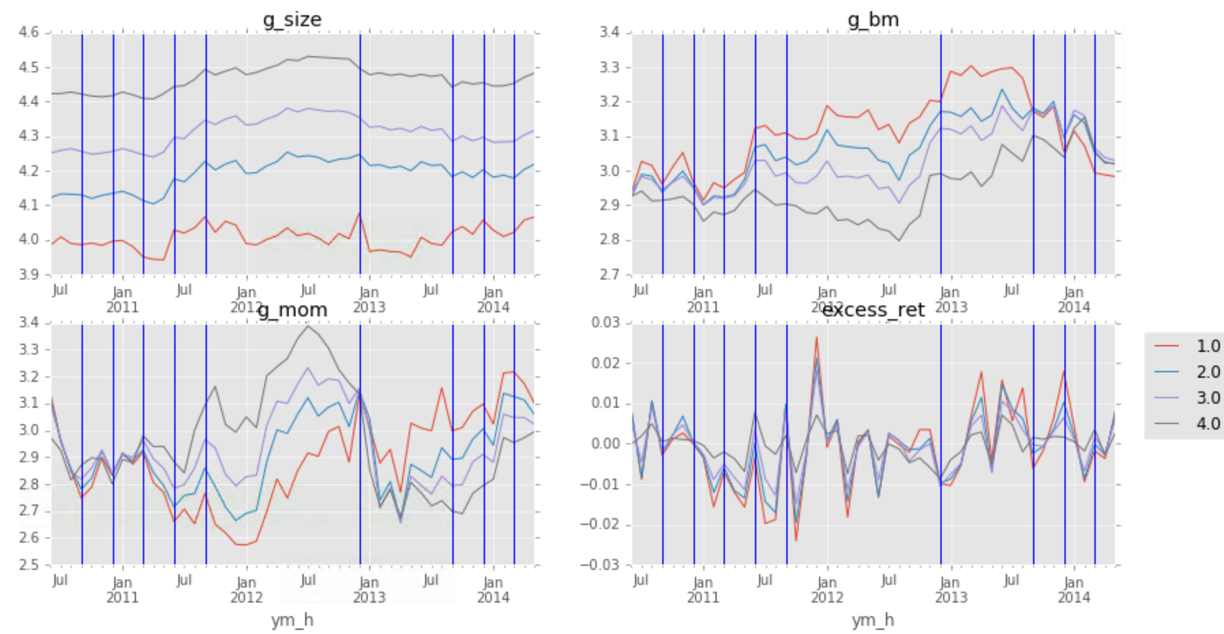


Figure 16. *Momentum Returns by Intensity of Retail Trading for Retail Initiated Trades Identified Through the Algorithm of Boehmer et. al. (2021), 2010-2021 Period*

Each month, we sort firms into 5 groups based on their cumulative returns from t-12 to t-2 (horizontal dimension). Then, within each of these groups, we form 5 sub-portfolios based on gross retail activity (the sum of retail buys plus retail sells divided by total trading volume) over the same t-12 to t-2 period. We identify retail flows using the algorithm of Boehmer et. al. (2021). Each bar represents the average monthly return (in %) for each of these 25 groups in month t.

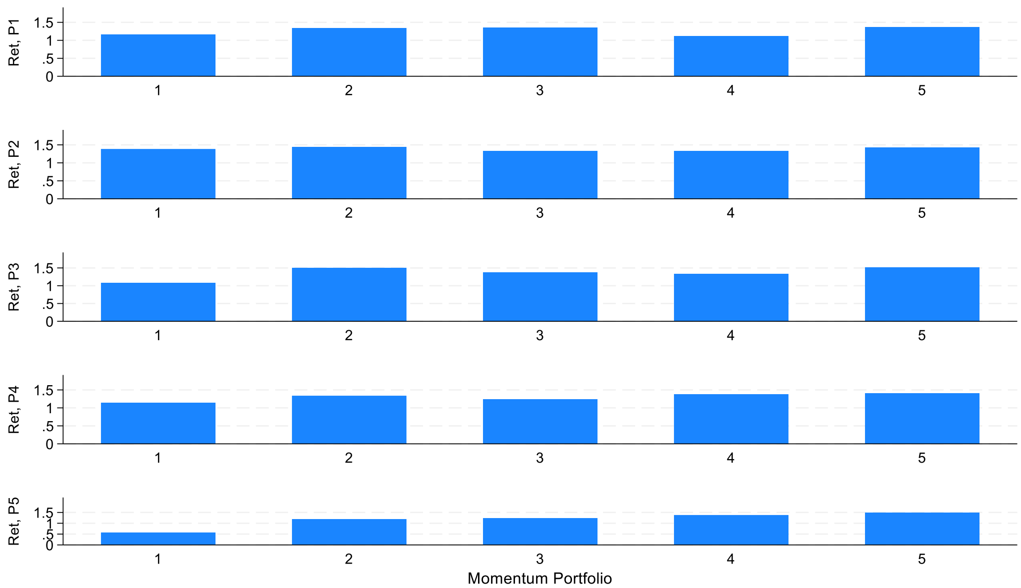


Figure 17. *Cumulative Returns by Size of the Earnings Surprise and Gross Retail Flows Identified Through the Algorithm of Boehmer et. al. (2021), 2010-2021 Period*

Each month, we sort firms into 5 portfolios based on their gross retail trading activity (the sum of retail buys plus retail sells divided by total trading volume). We identify retail flows using the algorithm of Boehmer et. al. (2021). Then, we examine earnings announcements in the following month, and form 5 portfolios based on standardized unexpected earnings (SUE). The left panel of the figure below shows the cumulative returns from day t-22 to day t+22 around earnings announcements for stocks which had the lowest gross retail activity over the prior month (the bottom quintile), while the right panel shows the same quantity for stocks which had the highest gross retail activity (the top quintile) over the prior month.

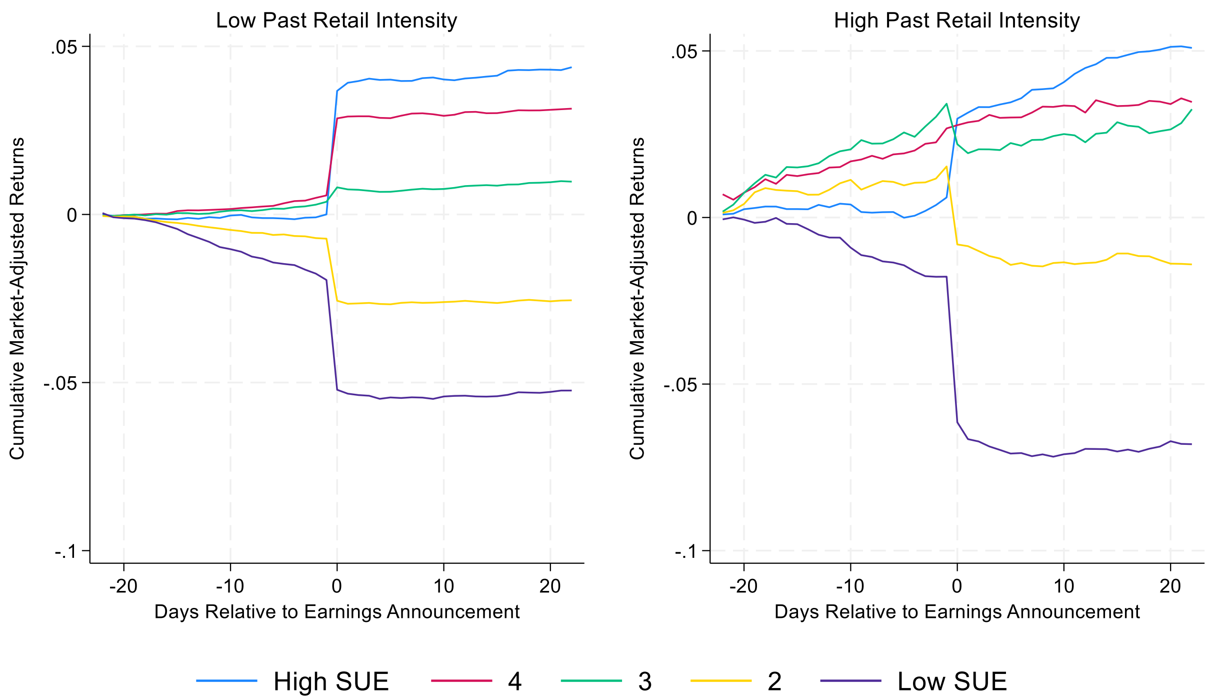


Figure 18. *Cumulative Returns by Size of the Earnings Surprise and Net Retail Flows Identified Through the Algorithm of Boehmer et. al. (2021), 2010-2021 Period*

Each month, we sort firms into 5 portfolios based on the magnitude of their standardized unexpected earnings (SUE). Then, we form 5 sub-portfolios based on the net retail trading activity from day t=0 to day t=22 i.e., after the earnings announcement (the difference of retail buys and retail sells divided by total trading volume). We identify retail flows using the algorithm of Boehmer et. al. (2021). The left panel of the figure below shows the cumulative returns from t=0 to t+22 around earnings announcements for stocks which in the lowest quintile of SUE, while the right panel shows the same quantity for stocks in the highest quintile of SUE.

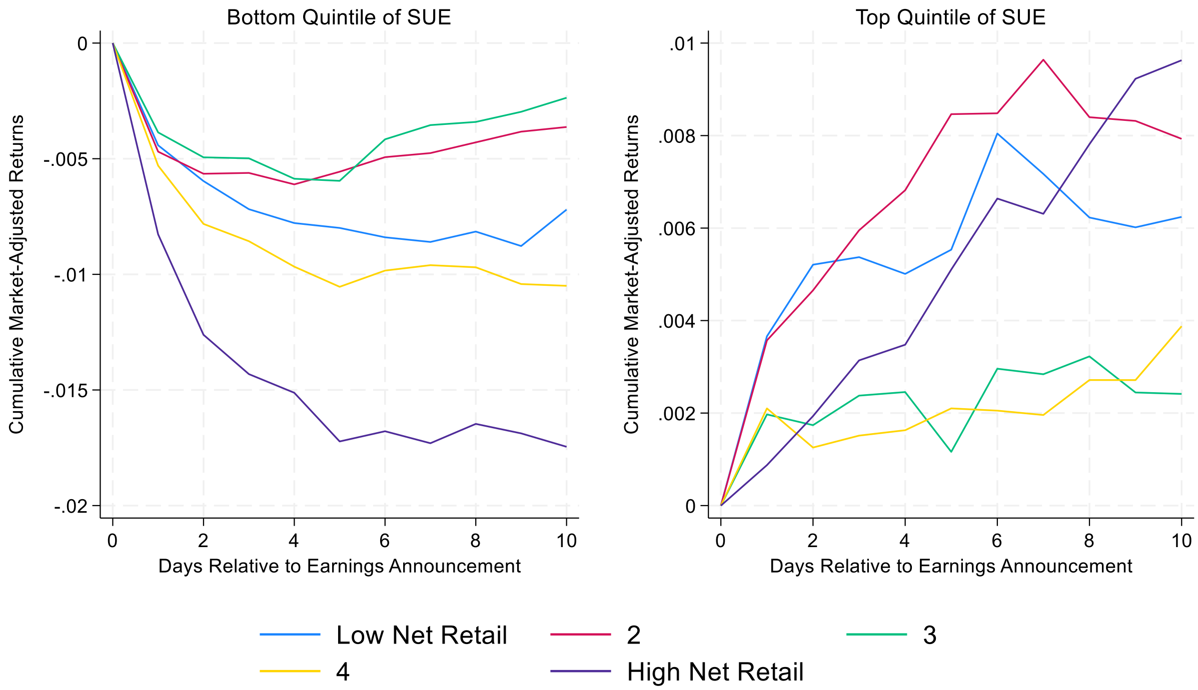


Table 1. *Descriptive Statistics: Account Holdings and Trading Frequency*

The tables below report descriptive statistics on account holdings and trading frequency of retail brokerage accounts from one of the largest U.S. discount brokers. The data include quarterly holdings and daily transactions for the majority of its clients between 2010Q2 – 2014Q. Panel A reports number of accounts and portfolio size. Panel B summarizes account holdings by security type. Panel C summarizes account trading frequency.

Panel A - Number of Accounts and Portfolio Size

	# Accounts		Portfolio Size			
Account Type	Count	Pct.	Amount ($M)	Pct.	Median ($)	Mean ($)
Individual: Taxable	1,658,547	58.50%	$ 135,096	49.50%	$ 7,407	$ 81,454
Individual: Retirement	882,022	31.10%	$ 69,934	25.60%	$ 24,090	$ 79,288
Organization	266,824	9.40%	$ 64,878	23.80%	$ 22,650	$ 243,150
Foreign	27,043	1.00%	$ 3,163	1.20%	$ 12,922	$ 116,954
Total	2,834,436	100.00%	$ 273,070	100.00%		

Panel B - Account Holdings by Security Type (as of June 30, 2014)

	# of Securities						
Account Type	Stock	Option	Bond	Mutual Funds	Warrant	Units	All
Individual: Taxable	6.08	0.33	0.07	0.17	0.03	0.00	6.67
Individual: Retirement	6.09	0.27	0.09	0.47	0.02	0.00	6.95
Organization	8.06	0.50	0.27	0.44	0.03	0.00	9.30
Foreign	5.90	0.70	0.05	0.05	0.02	0.00	6.73
Median Position Size ($)	$2,891	$396	$16,039	$7,931	$148	$146	$7,931
Total Position ($M)	$246,591	$2,309	$7,579	$18,337	$145	$10	$273,070

Panel C - Account Trading Frequency

	25th %tile	Median	75th %tile	Mean	SD
Pct Months Traded	8.2%	20.4%	48.9%	31.4%	29.2%
Monthly Turnover	2.0%	6.4%	22.6%	44.3%	138.0%
Trade Size ($)	$1,671	$3,859	$8,855	$9,825	$33,090

Table 2. *Descriptive Statistics: Account Holder Demographics*

The table and the map below report descriptive statistics on demographics of account holders. Panel A reports the breakdown by gender and mean and median age. Panel B plots the geographic distribution of accounts by portfolio value at the county-level. Counties with darker color are those with higher aggregate portfolio values.

Panel A - Gender and Age

Gender	# Accts	% Accts
Male	1,839,381	65%
Female	722,628	25%
N/A	278,084	10%
Total	2,840,093	100%
	Age	
Mean	46.9	
Median	49.0	

Panel B - Geographic Distribution: Portfolio Value

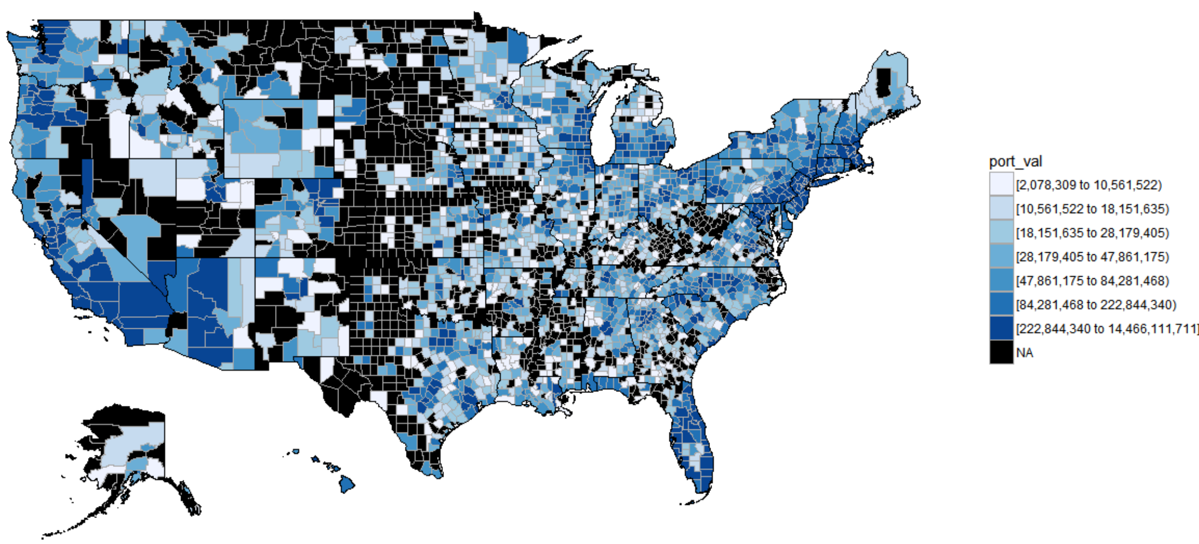


Table 3. *Disposition Effect: Odean (1998) Replication*

This table reports estimated disposition effect in our retail investors dataset using a methodology similar to Odean (1998). *Pct. Loss (Gain) Realized* is calculated as number of stock positions that were sold at a loss (gains) divided by total number of stock positions that had losses (gains), both realized and on paper. A negative difference between PLR and PGR suggests accounts are more likely to realize a loss than a gain, i.e. disposition effect. The t-statistics is reported below.

	This Paper	Odean (1998)
Pct. Loss Realized (PLR)	15.2%	9.8%
Pct. Gain Realized (PGR)	19.5%	14.8%
Difference	-4.3%	-5.0%
t-stat	39.3	35.0

Table 4. *Contrarian Behavior and the Disposition Effect*

Add legend here

	(1)	(2)	(3)	(4)	(5)	(6)
	All	All	All	Only roundtrip trades	No roundtrip trades	All
Gain	-0.00376		-0.00366	0.0165	-0.00468	-0.00361
	[-0.287]		[-0.271]	[1.108]	[-0.346]	[-0.271]
Positive Surprise		0.0116***	0.0146**	0.306***	-0.0187***	0.0157**
		[6.338]	[2.131]	[17.87]	[-2.877]	[2.325]
Gain * Positive Surprise			-0.00609	-0.0552***	0.015	-0.00611
			[-0.554]	[-3.375]	[1.380]	[-0.561]
Other Positive Surprises						0.0405***
						[6.428]
Gain * Other Positive Surprises						-0.00831
						[-1.431]
Constant	0.0920***	0.0892***	0.0915***	0.180***	0.0877***	0.0904***
	[11.21]	[1,049]	[10.86]	[20.23]	[10.38]	[10.94]
Observations	5,023,032	5,022,816	5,022,326	213,733	4,808,593	5,022,326
Adjusted R-squared	0.199	0.199	0.199	0.282	0.188	0.199

Table 5. *Firm-level Contrarian Index*

This table reports regressions of the fraction of contrarian trades by earnings surprise on firm characteristics. *Market β* is the CAPM beta obtained by regressing firm monthly excess returns on the market excess return, *Dividend yield* is the ratio of dividends per share to the share price, *Past return* is the stock return from t-12 to t-2, *Liquidity* is Kyle's (1985) lambda, measuring the volume required to move the stock price by one dollar. Higher values of lambda imply lower levels of liquidity, *Book-to-Market ratio* is the book market of equity divided by the market value of equity, *Gross Profitability* is the ratio of gross profits (revenues - cost of goods sold) to firm assets, *Leverage* is the ratio of long-term debt to book equity, *# of Analysts* is the number of security analysts covering the stock, *Institutional ownership* is the fraction of company shares owned by 13F institutional investors. All firm variables are lagged one month i.e. they are from the last month before the earnings announcement. Column (1) to (4) report the results for contrarian sales, while Columns (5) to (8) report the results for contrarian buys. The t-statistics are reported in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Sales	Sales	Sales	Sales	Buys	Buys	Buys	Buys
Market β		0.0250***	0.0242***	0.0228***		0.00697	0.00760	0.00797
		[4.811]	[4.522]	[4.232]		[0.950]	[1.020]	[1.062]
Dividend yield		-0.311**	-0.456***	-0.458***		2.274***	2.010***	2.038***
		[-2.366]	[-3.217]	[-3.231]		[13.15]	[10.83]	[10.97]
Past return		-0.0271***	-0.0264***	-0.0236***		-0.0204**	-0.0114	-0.00919
		[-4.002]	[-3.721]	[-3.249]		[-2.105]	[-1.126]	[-0.883]
Liquidity		-342.3	-622.0	-730.8		-538.3	-1,209**	-1,255**
		[-0.693]	[-1.240]	[-1.453]		[-0.895]	[-2.004]	[-2.079]
Assets			-8.90e-08	-8.07e-08			3.80e-07**	3.63e-07**
			[-0.886]	[-0.803]			[2.468]	[2.360]
Book-to-Market ratio			0.0210***	0.0199***			-0.00913	-0.00751
			[3.422]	[3.227]			[-1.081]	[-0.885]
Gross Profitability			0.00276	0.00138			-0.0429***	-0.0417***
			[0.275]	[0.137]			[-2.951]	[-2.866]
Leverage			0.00503***	0.00503***			-0.000105	-0.000143
			[2.675]	[2.671]			[-0.0390]	[-0.0528]
# of Analysts			-0.00134***	-0.00135***			0.00242***	0.00243***
			[-3.236]	[-3.249]			[4.059]	[4.075]

Institutional ownership			0.00363	0.00545			-0.0724***	-0.0720***
			[0.396]	[0.594]			[-5.660]	[-5.630]
log(Market Cap)			0.00255	0.00250			-0.0203***	-0.0200***
			[1.204]	[1.179]			[-6.881]	[-6.788]
Year 2010	0.474***				0.539***			
	[155.3]				[121.9]			
Year 2011	0.471***				0.538***			
	[209.0]				[170.9]			
Year 2012	0.473***				0.536***			
	[205.4]				[171.5]			
Year 2013	0.459***				0.515***			
	[201.3]				[166.5]			
Year 2014	0.459***				0.536***			
	[144.2]				[129.7]			
Constant		0.459***	0.421***	0.422***		0.480***	0.819***	0.812***
		[59.59]	[13.51]	[13.55]		[43.43]	[19.05]	[18.85]
Observations	46,112	16,442	16,158	16,158	14,855	4,834	4,751	4,751
Adjusted R-squared	0.788	0.003	0.005	0.005	0.888	0.040	0.063	0.065

Table 6. *Contrarian Behavior and Company Earnings: the Role of Attention*

This table reports horizon effect of contrarian trading around company earnings. Dependent variable is *Is Sold (Bought)*, indicating whether an account sold (bought) the stock during the first five trading days since earnings announcement. *Earnings Ret* is cumulative stock return during first five trading days since earnings announcement. *Is Visit* is a dummy variable indicating whether an account looked up the stock on the research page before the earnings. The sample is close to 11,000 random individual accounts that have web click data from June 2013 to June 2014. Robust standard errors are reported below estimated parameters.

	Is Sold (1)	Is Sold (2)	Is Sold (3)	Is Bought (4)	Is Bought (5)	Is Bought (6)
Earnings Ret	0.922***	0.957***	0.838***	-0.818***	-0.798***	-0.676***
	(0.247)	(0.248)	(0.263)	(0.174)	(0.174)	(0.186)
Is Visit		0.019***	0.018***		0.011**	0.011**
		(0.007)	(0.007)		(0.005)	(0.006)
Is Visit x Earnings Ret			1.033			-1.049**
			(0.795)			(0.514)
Intercept	0.040***	0.037***	0.037***	0.029***	0.027***	0.027***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
N	10407	10407	10407	10400	10400	10400
R2	0.003	0.004	0.004	0.004	0.004	0.005

Table 7. *Contrarian Behavior and Company Earnings: Horizon Effect*

This table reports horizon effect of contrarian trading around company earnings. Dependent variable is *Is Sold*, indicating whether an account sold the stock during the first five trading days since earnings announcement. *Earnings Ret* is cumulative stock return during first five trading days since earnings announcement. *Earnings Ret x Month = i* is an interaction term between earnings announcement return and whether an account accumulated the stock positions in i months before the company earnings. *Month = 0* means that the account bought the stock in the same month as the company's earnings. The sample is 500,000 random individual accounts from June 2010 to June 2014. t-stats based on robust standard errors are reported below estimated parameters.

	Is Sold							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Earnings Ret	0.628***	0.510***	0.494***	0.498***	0.510***	0.497***	0.556***	0.657***
	(18.9)	(15.3)	(15.3)	(15.0)	(15.2)	(15.4)	(16.7)	(16.5)
x Month = 0	-0.674***							
	(6.9)							
x Month = 1		0.225**						
		(2.2)						
x Month = 2			0.546***					
			(4.1)					
x Month = 3				0.430***				
				(4.0)				
x Month = 4					0.275***			
					(2.8)			
x Month = 5						0.607***		
						(4.3)		
x Month = 6							-0.182*	
							(-1.80)	
x Month = 7+								-0.415***
								(-6.75)
Intercept	0.0258***	0.0257***	0.0256***	0.0256***	0.0256***	0.0256***	0.0256***	0.0256***
	(105.9)	(106.1)	(106.4)	(106.4)	(106.3)	(106.4)	(106.4)	(106.4)
N	436637	436637	436637	436637	436637	436637	436637	436637
R2	0.0017	0.00147	0.00156	0.00153	0.00148	0.00157	0.00145	0.00162

Table 8. *Account-level Factor Regressions: Fama-French 3-Factor Model with Momentum*

This tables below report the distributions of factor loadings and excess returns from account-level factor regressions. For each account with at least 12 months of return history and account balance above $1000, we conduct a time-series factor regression using Fama-French 3-factor model with momentum. Panel A reports distributions of estimated factor loadings and excess return across different accounts. Weighted average is based on beginning balance in the sample period. Panel B reports distributions only for estimates that have p-value smaller than 0.1.

Panel A - Full Sample

	Mean	Weighted Mean	Cross-Acct SD	25th %tile	50th %tile	75th %tile	N
MKT	0.95	0.93	0.51	0.68	0.94	1.19	2,399,149
SMB	0.22	0.08	1.02	-0.36	0.08	0.72	2,399,338
HML	-0.14	-0.14	0.96	-0.58	-0.07	0.33	2,397,796
MOM	-0.23	-0.15	0.83	-0.59	-0.15	0.14	2,397,495
Intercept	-0.0027	-0.0022	0.0146	-0.0083	-0.0016	0.0036	2,398,778

Panel B - Significant Sample

	Mean	Weighted Mean	Cross-Acct SD	25th %tile	50th %tile	75th %tile	N
MKT	0.8	0.79	0.69	0.42	0.66	1.23	591,262
SMB	0.43	0.07	1.4	-0.68	0.5	1.46	612,028
HML	-0.24	-0.33	1.37	-1.18	-0.49	0.79	508,148
MOM	-0.59	-0.34	0.97	-1.11	-0.65	-0.15	638,661
Intercept	-0.0119	-0.0093	0.0236	-0.0258	-0.0131	-0.0022	269,307

Table 9. *Factor Tilts: 1-way Account Grouping*

(A) By Account Balance

	MKT		SMB		HML		MOM		Intercept	
Balance ($)	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean
1k-10k	1.06	1.14	1.11	0.81	0.17	-0.09	-0.87	-0.77	-0.02	-0.02
10k-100k	0.99	1.03	0.42	0.34	-0.55	-0.31	-0.58	-0.53	-0.01	-0.01
100k-1m	0.94	0.97	-0.40	-0.05	-0.47	-0.36	-0.32	-0.28	-0.01	-0.01
>=1m	0.94	0.98	-0.42	-0.19	-0.33	-0.28	-0.17	-0.16	-0.01	0.00

(B) By Trading Activity

	MKT		SMB		HML		MOM		Intercept	
# Trades/Mo	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean
Stocks [0, 0.5)	0.99	1.03	0.19	0.31	-0.27	-0.08	-0.60	-0.52	-0.01	-0.01
Stocks: [0.5, 1)	0.99	1.05	0.43	0.40	-0.55	-0.31	-0.63	-0.58	-0.01	-0.01
Stocks: [1, 10)	1.02	1.10	0.74	0.64	-0.72	-0.53	-0.71	-0.67	-0.01	-0.01
Stocks: [10, ∞)	1.18	1.30	1.50	1.29	-1.14	-0.87	-1.08	-0.95	-0.02	-0.02
Options: [0.5, ∞)	1.06	1.15	1.01	0.80	-0.92	-0.65	-0.86	-0.81	-0.02	-0.02

(C) By Account Type

	MKT		SMB		HML		MOM		Intercept	
Acct Type	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean
foreign	1.12	1.20	1.01	0.77	-0.72	-0.34	-0.90	-0.88	-0.02	-0.02
individual	1.03	1.09	0.75	0.58	-0.47	-0.20	-0.71	-0.66	-0.01	-0.01
organization	0.95	1.00	-0.39	0.09	-0.42	-0.23	-0.42	-0.37	-0.01	-0.01
retirement	0.97	1.02	-0.15	0.30	-0.53	-0.30	-0.59	-0.51	-0.01	-0.01

Table 10. *Retail ETF Net Purchases around Macroeconomic News*

This table reports retail ETF trading activities around macroeconomic news announcements. *Is Good News* is a dummy variable indicating when released data is better than professional survey estimates. Dependent variable is SP return in Column (1), aggregate retail net inflow into equity market in Column (2), retail net inflow into SPY in Column (3) and retail net inflow into GLD in Column (4). Time horizon for return and flow is the announcement day itself. Year-month fixed effects are included.

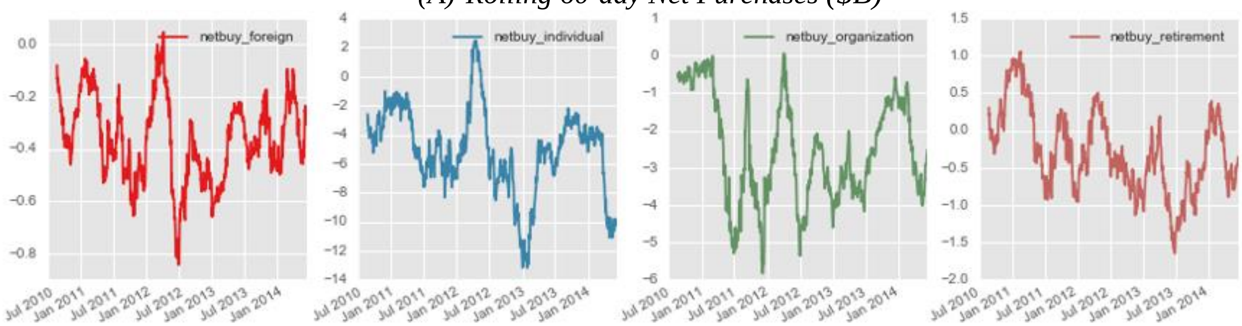
	SP Return	Net Inflow: All	Net Inflow: SPY	Net Inflow: GLD
	(1)	(2)	(3)	(4)
Is Good News	0.017	-0.144	-0.096	-0.017
	(0.001)***	(0.010)***	(0.031)***	(0.046)
Constant	-0.002	-0.014	0.043	-0.016
	(0.001)***	(0.005)**	(0.011)***	(0.026)
N	967	967	967	967
R2	0.379	0.278	0.029	0.005

APPENDIX

Figure A1. *Aggregate Retail Net Purchases*

The graphs below show aggregative net purchases of retail investors for individual taxable accounts, individual retirement accounts, foreign accounts, and organization accounts. Panel (A) plots rolling 60-day net inflow. Panel (B) plots cumulative net purchases.

(A) Rolling 60-day Net Purchases ($B)



(B) Cumulative Net Purchases ($B)

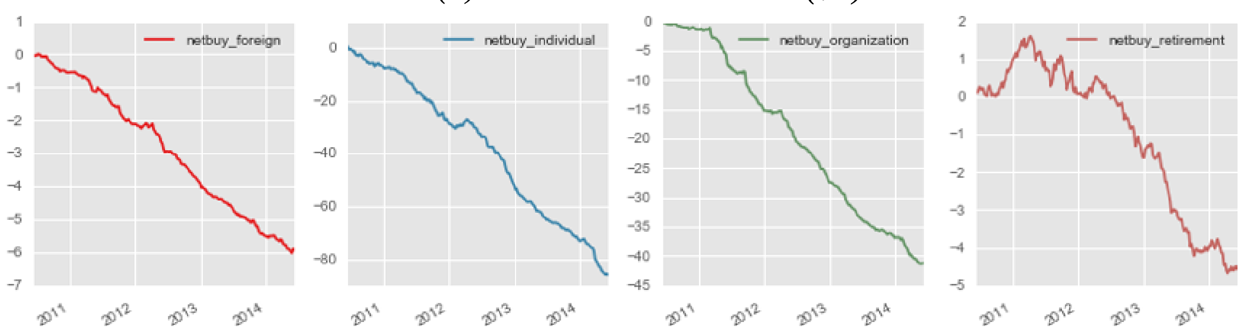
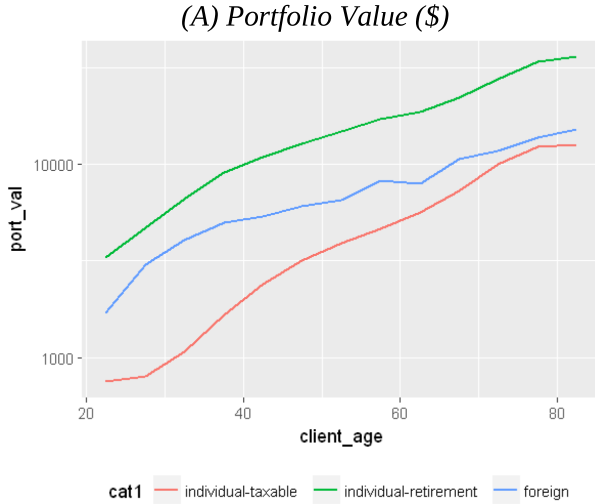
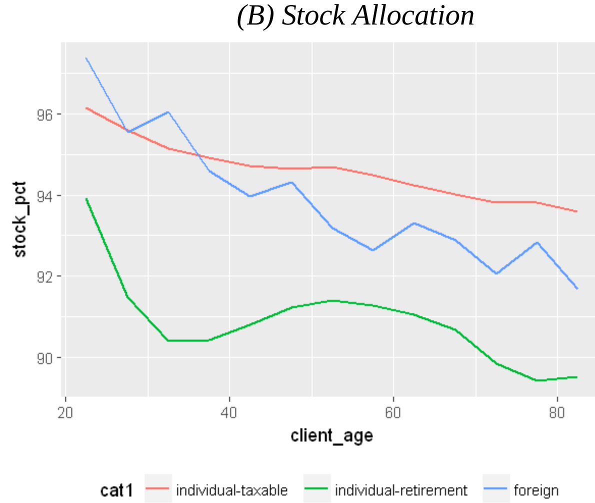


Figure A2. *Account Holdings and Asset Allocation by Age*

(A) Portfolio Value ($)



(B) Stock Allocation



APPENDIX

Table A1. *Contrarian Trading Around Earnings*

This table reports estimated sensitivities of selling and buying activities to stock returns during earnings announcement. Dependent variable is *Is Sold (Is Bought)*, indicating whether an account sold (bought) the stock during the first five trading days since earnings announcement. *Earnings Ret* is cumulative stock return during first five trading days since earnings announcement. *Is Gain* is a dummy variable indicating whether an individual account has embedded gains in the stocks reporting earnings. The embedded gain is calculated as the difference between the pre-earnings price and the cost basis. The cost basis is based on the average purchase price for trades before the earnings. The sample is 500,000 random individual accounts from June 2010 to June 2014. Robust standard errors are reported below estimated parameters.

	Is Sold	Is Sold	Is Bought	Is Bought
	(1)	(2)	(3)	(4)
Earnings Ret	0.541	0.829	-0.627	-0.595
	(0.026)	(0.058)	(0.024)	(0.043)
Earnings Ret x Is Gain		-0.459		-0.050
		(0.069)		(0.051)
Intercept	0.026	0.027	0.018	0.018
	(0.000)	(0.000)	(0.002)	(0.000)
N	440573	440573	440573	440573
R2	0.0016	0.0016	0.003	0.003