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

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Abstract

Using a large panel of U.S. accounts trades and positions, we show that retail investors trade as contrarians after large earnings surprises, especially for loser stocks, and such contrarian trading contributes to post earnings announcement drift (PEAD) and 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 momentum. The results on the timing of the flows and the magnitude of the return differences across momentum portfolios by retail trading intensity and size and sign of the earnings surprise, are confirmed at a longer two-year horizon. Alternative hypotheses, such as the disposition effect and stale limit orders, do not explain the phenomenon. We find that younger investors and day traders are more likely to be contrarians, while gender and number of trades are not correlated with our contrarian score, once other characteristics are controlled for. The pattern of web-clicks and the time spent analyzing each stock on the brokerage platform suggest an important role of attention in contrarian trading.

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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. The stocks of companies that have announced abnormal positive (negative) earnings tend to outperform (underperform) going forward stocks with smaller or no earnings surprises (Ball and Brown 1968, Bernard and Thomas 1989, 1990). 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). Recent research argues that price momentum and earnings 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 in the period 2010-2014, we document that retail investors tend to trade as contrarians around news announcements, selling stocks on large positive earnings surprises, and buying stocks on negative large earnings surprises. We find evidence of contrarian behavior even after controlling for recent price changes and that such contrarian trading contributes to sluggish price adjustment and to momentum.

The magnitude of the retail trading activity around large earnings surprises in our results suggests a significant role of retail investors in generating momentum and slow price adjustment. Consistent with our hypothesis, when we double-sort stocks based on the intensity of contrarian retail trading and past returns we find that the momentum phenomenon is concentrated in the top two quintiles of retail trading intensity, while it is non-existent elsewhere.

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 for holding periods between a month and a year. Third, it is related to investors' attention to a stock, as measured by the frequency with which investors log into their accounts to check news on the stocks they hold, which we can observe for a random sample of eleven thousand accounts.

In addition, we find that the results are concentrated among losers and small stocks, consistent with the findings in Hong, Lim, and Stein (2000), and we confirm in our dataset that more than 50% of the stocks enter the momentum portfolios due to (strings of) large positive or negative earnings surprises, as shown by Chan, Jagadeesh and Lakonishok (1996).

Alternative explanations of our findings include the disposition effect, the tendency to sell winners and hold on to losers, and the presence of limit orders based on stale prices. While we confirm the presence of the disposition effect among our individual investors, we show that around earnings surprises the individuals who trade tend to be contrarians and sell (buy) the stocks after a positive (negative) earnings surprises, regardless of the presence of a capital gain and its size. Similarly, our results are confirmed if we restrict our attention to market orders for which stale prices are not an issue.

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 correlated with 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.

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, stock specialization and infrequent trading 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.

Our results 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 are able to 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.

Finally, we show that on balance retail investors have been decreasing their holdings of individual stocks over our sample period. This in turn implies institutional and professional investors represent an increasing fraction of stock trading. Thus, 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.

Our research raises the question of what drives retail contrarian trading behavior in response to news. One potential interpretation is that investors exhibit a disposition effect (Shefrin and Statman, 1985). We document that indeed the investors in our sample exhibit a disposition effect similar to the one documented by Odean (1998) for different groups of individual investors: When not trading around earnings surprises, investors tend to prioritize in their stock sales stocks with embedded capital gains over stocks with embedded losses, and some of the trading around earnings surprises does involve stocks with high embedded capital gains. Moreover, the disposition effect cannot explain the tendency to buy on negative news.

A potential explanation for this contrarian trading behavior in response to news is that these investors believe in mean reversion in stock prices or, more specifically, that they believe that markets over-react to news as a result of other investors excessive optimism or pessimism. Their contrarian trading on earnings announcements follows from their desire to take advantage of their perception that markets over react to news. This hypothesis is not entirely implausible: The belief that markets over-react is very extended among all types of investors, and it is arguably the predominant view of market behavior of both market pundits and the popular media. Moreover, investors who open and maintain a brokerage account are more likely to exhibit over-confidence in their trading ability (Daniel, Hirshleifer, and Subrahmanyam, 1998) and might hold stronger views about mean reversion than the overall population of investors. Investors with such beliefs are likely to trade against news, particularly significant news. In recent work, Bastianello and Fontanier (2019) posit a general equilibrium asset pricing model of partial equilibrium thinking in which uninformed investor contrarian trading behavior is consistent with equilibrium. In their model, uninformed agents will rationally trade contrarian if they believe that other uninformed agents are overreacting to news but fail to internalize that other market participants might have the same beliefs and also act on them.

We also find that the investors in our sample hold portfolios that exhibit a negative exposure to the momentum factor or MOM (Carhart, 1997), consistent with prior studies of the factor exposure of individual investors' portfolios (Barber and Odean, 2002; Campbell, Ramadorai, and Ranish, 2014; Betermier, Calvet, and Sodini, 2017). However, we show that this negative exposure to MOM doesn't appear to be deliberate. We show that portfolio inertia is such that the factor characteristics of the portfolios held by these investors, measured using the methodology of Daniel, Grinblatt, Titman, and Wermers (1997), vary over time as the characteristics of the stocks they hold shift over time. This is particularly significant for MOM, since it is a stock characteristic which, unlike size or value, changes over time relatively quickly.

The remainder of the paper is organized as follows. Section II describes the data and some summary statistics. Section III explores the performance and the portfolio characteristics of the portfolios held by the investors in our dataset. Section IV investigates the trading behavior of individual investors upon the release of information. Section V explores the relation between retail trading and the momentum effect. Section VI discusses alternative explanations for the findings, beyond the disposition effect. Section VII reports our results on contrarianism following macroeconomic news. Section VIII concludes.

II. Data and Summary Statistics

Investor Data

The source of our 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 the accounts. Panel A 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 retirement accounts, 267 thousand (9.4%) are institutional accounts, and 27 thousand are owned by foreigners. The value of the assets in the accounts is $273 billion.

The vast majority of the accounts are individual accounts, which also hold most of the assets. 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 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.

The upper panel of Figure 1 shows the time series of rolling 60-day aggregate net purchases in NYSE, AMEX, and NASDAQ stocks for each type of account, taxable, retirement, foreign-owned, and institutional, over our sample period, while the lower panel shows the cumulative net purchases. These are about 5,300 common stocks that account for 69.4% of total trading volume in the sample. We compute aggregate net 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%).[1] The age distribution is bell shaped, and peaks at 43 years old. Figure A1 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

To construct a complete picture of one's asset holdings, we link investors' holdings and transactions data across various financial datasets by constructing a comprehensive security master

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

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

We also construct a comprehensive event database, of both corporate events and macroeconomic news, and merge it with investors' holding and transaction data. We use COMPUSTAT and I/B/E/S to extract financial information and analyst earnings expectations about the companies in the dataset, and Capital IQ Key Developments and Bloomberg News Calendar to extract data on company news and macroeconomic announcements.[2] Tables A2 and A3 in the Appendix provide a comprehensive list of the types of company news and macroeconomic news available from our data sources. Earnings announcements, together with company presentations, are the most frequent company events, comprising 10.3% and 13.3% of the sample, respectively. To link the same security across multiple datasets, we use the unique identifier of the issuing company. For company events, we infer whether it is positive or negative news based on contemporaneous market reaction. For macroeconomic events, we infer whether it is good or bad news by comparing actual released values to prior or consensus values.

By combining the investors' holdings and transactions data with the return, financial, and event data as well as the account holders' demographics, we construct a flexible and comprehensive database to allow various empirical tests of household trading and asset allocation hypotheses.

III. Individual Investors' Equity Portfolio Characteristics and Performance

Prior to examining investors trading behavior in response to news, it is important to understand the characteristics of their portfolios, and how they evolve over time. In order to do that, we build daily portfolio holdings and end-of-day balances for each account using the initial snapshot of portfolio balances in our dataset, daily transactions, and our matched pricing data, after adjusting

[2] We are grateful to John Zhou for providing us with a comprehensive database of macroeconomic news announcements.

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.

As previously noted, we limit attention to the equity component of portfolios. This includes holdings of both individual stocks included in CRSP and 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.

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 3 reports the distribution of the coefficients at the account-level factor regressions. 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 3 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. This suggests that on average retail investors do not have portfolios tilted toward high beta stocks. 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. However, factor exposures exhibit considerable cross-sectional variation across accounts.

The distribution of factor exposures shows that the anti-momentum exposure is pervasive across the sample. At least 75% of the accounts exhibit a negative exposure to momentum. Moreover, Table A1 in the Appendix shows that 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. The magnitude of the negative exposure to momentum is strongly negatively correlated with account size, and positively correlated with trading activity.

Table 3 shows that the estimated intercept or "alpha" in factor regressions at the individual account level is not statistically different from zero for most of the 2.4 million accounts. About 270 thousand of them exhibit intercepts statistically different from zero. These non-zero alphas are pervasively 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. Only the top 10% of the accounts with non-zero alphas exhibit a positive alpha. That is, the vast majority of investors in our sample do not exhibit 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 balances that particular month. 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 2 shows 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 A3 in the Appendix 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.

IV. Retail Investor Trading Around Company News

We focus on the analysis of investor behavior around earnings announcements for three reasons. First, earnings announcements are arguably one of the most important pieces of information companies release about their performance and financial health. Moreover, companies release information about their earnings with relatively high frequency. Earnings announcements, together with company presentations, is the single most frequent piece of company news (Table A2). Second, it is an important piece of information for which we have good measures of expectations from market participants. Third, unlike other types of news, the sign of the impact of earnings surprises on stock prices is unambiguous, particularly for large surprises.

Measuring Earnings Surprises

Following standard practice in the literature, we measure earnings surprises as realized earnings per share relative to consensus analyst forecasts, and scale this difference by the stock price at the time of the announcement. 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.

This definition implies that we have to limit our empirical analysis of investor behavior around earnings announcements to stocks with analyst coverage. As previously noted, stocks account for more than 90% of assets held by investors in the sample, and most publicly traded stocks have analyst coverage. If anything, this sample selection likely biases the results against our findings, as small loser stock with low analyst coverage are more likely to display momentum and to be held by retail investors (Hong, Lim, and Stein, 2000).

Retail Investor Contrarian Behavior Around Company News

Table 4 examines the behavior of retail trading around earnings announcements for a random sample of 500 thousand individual accounts from June 2010 through June 2014. Columns (1) and (2) in Panel A of the table examine selling behavior, and columns (3) and (4) examine buying behavior.

Column (1) shows the results of a pooled regression of an indicator variable that takes a value of 1 if an account sold a stock during the first five trading days since earnings announcement onto the cumulative stock return during the same period. The regression coefficient is positive and economically and statistically highly significant. Column (3) shows the same regression for an indicator variable of buying behavior defined in an analogous manner to the indicator variable for selling behavior. The regression coefficient is negative and also statistically and economically highly significant. Taken together, these results suggest that individual investors tend to sell if earnings announcements are positive, and to buy if they are negative. The intensity of their contrarian selling or buying behavior is directly related to the magnitude of the earnings announcement return.

Our results are consistent with the finding in Kaniel at al. (2012) that the buying and selling volume of executed orders from individuals in the NYSE is negatively correlated with the sign of earnings announcement returns. Our results are also consistent with Grinblatt and Keloharju (1999) who document that Finnish households trade as contrarians with respect to past returns.

The contrarian selling behavior—although not the buying behavior—of the investors in our sample is consistent with the disposition effect documented by Odean (1998). The disposition effect alludes to the preference of investors to prioritize assets with embedded capital gains over those with capital losses when they engage in selling, whichever motive triggers their desire to sell, even though this is generally tax inefficient. However, the contrarian buying behavior of the investors in our sample is hard to reconcile with the disposition effect.

To test whether the disposition effect drives all the selling behavior in our sample, Column (2) in Panel A of Table 4 introduces an additional control in the selling behavior regression, which is a dummy variable indicating whether an individual account has embedded gains in the stocks reporting earnings interacted with the earnings announcement return .[3] The regression coefficient on the interaction is negative and statistically highly significant, suggesting that investors exhibit a less intense contrarian selling behavior for stocks with embedded capital gains. Stock sales for contrarian reasons appear less prone to suffer from the disposition effect, although the population of investors in our dataset at large does, as shown below.[4]

Panel B in Table 4 calculates the gains or losses from earnings-contrarian trading and compares them to those from trading for other reasons. The panel shows that investors tend to realize capital gains when they trade for contrarian reasons. Yet, such gains appear to be smaller than the paper gains of the investors who don't trade. These gains are also smaller when they are weighted by the size of the position, implying that they tend to realize smaller gains on the larger positions they sell.

[3] We calculate the embedded gain in a stock position as the difference between the pre-earnings price and the cost basis for that particular investor. The cost basis is based on the average purchase price for trades before the earnings. For positions that existed before our initial observation date we use the stock price at the start of the sample period as their cost basis and then combine it with trades in the sample period.

[4] For completeness, Column (4) runs the same regression for buying behavior. The coefficient on the interaction term is only slightly negative and statistically not different from zero, as one would expect.

The regression results in Table 4 suggest that the buying and selling behavior of individual investors in the face of news about earnings is independent of behavior induced by the disposition effect. This is not to say that the investors in our sample do not exhibit a disposition effect. Table 5 replicates the main analysis of this effect in Odean (1998) for our sample of investors. It also reproduces the results in the Odean (1998) study for ease of comparison. As the brokerage investors in Odean's sample of retail investors from the late 1980's and early 1990's, the investors in our sample exhibit a similar disposition effect. The number of stocks they sell at a gain as a fraction of all stocks with gains they hold is larger than the number of stocks they sell at a loss as a fraction of all stocks with losses. That is, unconditionally the investors in our sample still exhibit a preference for selling stocks with embedded gains over those with embedded loses when they sell. This difference is statistically significant, and the magnitude of the effect appears to be larger in our sample than in Odean's (1998) sample.

Table 6 shows the dispersion in buying and selling by the individual investors in our sample as a function of the magnitude and sign of earnings surprises. Panel A shows the percentage of accounts that buy and sell in the day of an earnings announcement and over the subsequent ten trading days, whether these accounts have traded or not the stock in the ten trading days before the earnings announcement, and the direction of the trade. Panel B shows the percentage of mean and median retail trading volume at the announcement day and over the subsequent ten days accounted for by buy orders and sell orders.

The table shows that, as expected, there is significant disagreement in retail trading, with both a large percentage of accounts buying and selling. But Panel A shows that there are more buyers than sellers when the earnings surprise is negative, and more sellers than buyers when it is positive. Panel B shows that the asymmetry between buying and selling behavior is stronger when we account for dollar trading volume by buyers and sellers, particularly with positive earnings surprises. For the most positive earnings surprises (quintiles 4 and 5), selling volume accounts for at least 54% of a stock's trading volume on average, and it represents at least 73% of the trading volume for the median stock.

Panel A of the table also shows that more than 96% of the accounts that trade on or after the announcement do not trade the stock during the ten trading days before the announcement. This suggests that the retail contrarian trading behavior we observe is not information driven on average, in the sense that these individuals trade in advance of the earnings announcement and then reverse their trades to realize gains.

Table 7 further explores whether the contrarian behavior documented in Table 4 is related to attention. Table 7 examines buying and selling behavior conditional on earnings announcements for a sub-sample of investors for whom we know activity on the trading platform. 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 (10 and (4) of Table 7 confirm that the contrarian selling and buying behavior is also present in this sample. The coefficient on the earnings announcement return is positive for the selling indicator variable and negative for the buying indicator variable. These coefficients are larger than those for the sample of 500 thousand random individual accounts, indicating that this contrarian behavior is, if anything, more intense for this sample.

The coefficient on the indicator variable of attention is positive and statistically significant in both the selling and buying, consistent with the positive relationship between trading and attention. Moreover, the coefficient on the interaction of this indicator variable with the earnings announcement return is positive in the selling regression and negative in the buying regression, and as large in magnitude as the coefficient on the earnings announcement return itself, suggesting for a given earnings announcement return the account is twice as likely to engage in contrarian trading when if the investor has looked up the stocks before the earnings announcement.

Table 8 explores the strength of the contrarian selling trading behavior 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 the investor has held the stock. For stocks held at the inception of the sample, we assume the stock was purchased on that date.

The results in Table 8 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.

An important question is what triggers retail investors contrarian trading behavior in the presence of new information. The results in this section are consistent with investors acting on the belief that the market overreacts to news, making optimal to buy upon the release of negative news and to sell upon the release of positive news.

The view that there is mean reversion in stock returns, or equivalently, that stock prices tend to overreact to news as the result of trading by unsophisticated investors who become too optimistic (or too pessimistic) in the presence of good (or bad) news is highly pervasive among sophisticated market participants and market pundits. The investors in our sample are investors who choose to open a brokerage account and trade actively. They might see themselves as sophisticated investors and believe that markets overreact. Consistent with this self-perception, they might think that they take advantage of less sophisticated investors by trading contrarian upon earnings announcements, particularly when earnings surprises are large. Inadvertently, however, they might in fact contribute to making prices *underreact* to news releases. We explore this hypothesis next.

V. Contrarian Trading Behavior on Individual Stocks and Momentum

Chan, Jegadeesh and Lakonishok (1996) find that prices tend to drift after earnings surprises in the same direction as the earnings surprise. More recent research (Chordia and Shivakumar, 2006; Novy-Marx, 2015) links price momentum to underreaction to earnings news. It shows that controlling for earnings surprises and earnings announcement returns, lagged 11-month returns excluding the most recent month do not appear to predict future intermediate-horizon returns, particularly in the most recent period 1993-2012.

Figure 3 provides a visual representation of the link between earnings news and price momentum documented in the literature for the stocks with earnings coverage held by the investors in our sample. The figure plots the average earnings surprise from 18 months before to 12 months after formation of five momentum portfolios during our sample period 2010-2014. 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 figure shows that the stocks in the momentum portfolios with the largest lagged returns exhibit positive earnings surprises which are significantly and consistently larger than those of the stocks in the momentum portfolios with smallest lagged returns. Moreover, the spread in the magnitude of earnings surprises between winners and losers widens as we approach the portfolio formation date. This spread narrows progressively after the portfolio formation date over a period of about one year. This pattern is not exclusive of the extreme momentum portfolios, but it is rather monotonic across all five momentum portfolios.

Consistent with the results in Chordia and Shivakumar (2006) and Novy-Marx (2015), Figure 3 suggests that the sorting of momentum stocks based on past returns is not independent of the sorting based on past earnings surprises. If prices underreact to earnings surprises and earnings surprises exhibit momentum, price momentum could be just a reflection of earnings momentum.

Figure 4 shows the percent of stocks entering the momentum portfolios which do not have earnings surprises in the portfolio formation period. This figure shows that at least 55% of the stocks in the extreme loser portfolio have earnings surprises. This percentage increases monotonically across momentum portfolios, and it is as large as 75% in the extreme winner portfolio.

We explore next whether the price momentum generated by earnings momentum is correlated with individual trading behavior.

We have shown evidence in Section III that the average individual account has a negative exposure to the momentum factor—in fact, 75% of the accounts with momentum exposure do. This negative exposure is even more pronounced for the accounts that exhibit more trading activity.

Furthermore, we have shown evidence in Section IV that the release of news tends to trigger contrarian trading in individual accounts. We have hypothesized that the contrarian trading behavior of the investors in our sample might be the result of these investors trying to exploit a belief that other investors systematically *overreact* to news. By trading contrarian, these investors might in fact contribute to make prices *underreact* to news.

Figure 5 provides supporting evidence that individual investors might contribute to momentum. It plots average total net inflow relative to total trading volume for the five momentum portfolios in the left panel, and average absolute flow relative to total trading volume on the right panel. The vertical lines show the 95% confidence interval of the null hypothesis of zero. The left panel shows that net inflow is positive and significantly different from zero for the loser portfolios, and negative and significantly different from zero for the winner portfolios. Retail investors on average buy negative momentum stocks and sell positive momentum stocks. The right panel in the figure shows that absolute flow is larger for the extreme momentum portfolios, particularly for the loser portfolio. Retail investors trade extreme momentum stocks more actively. The purchases and sales of the retail investors in our sample account for about 5% of market volume and 3% of market volume of the largest losers and winners, respectively. Although these figures might seem modest, the retail investors are a small fraction of the total population of retail investors with brokerage accounts. We elaborate on this point further below.

Figure 6 plots average net inflow relative to total trading volume as a function of the magnitude of earnings surprises. Each month we divide stocks in three groups based on the absolute magnitude of their average earnings surprises in the past four quarters. We then compute volume-adjusted net inflows and absolute flows into the stocks in each of the momentum portfolios. Net inflows into the extreme momentum portfolios appear to be more significant for those stocks experiencing large earnings surprises of both signs. The portfolio of past losers experiences positive net inflows, while the portfolio of past winners experiences negative net inflows.

In Figure 7 we provide further evidence of the role of retail contrarian trading for momentum by plotting the average return to twenty-five portfolios, sorted first by the trading intensity of the individual investors in our sample, and then based on past returns. The sample period is June 2010 through June 2014. We divide stocks in five quantiles according to the intensity to which the investors in our sample trade them. We then form momentum portfolios with the stocks in each trading intensity quantile. Table 9 provides further details on these findings. The table shows that there is no return spread in momentum portfolios for stocks with low retail trading intensity. If anything, the spread between winners and losers is negative, at -0.59% per month. By contrast, as we consider momentum portfolios built with stocks more intensely traded by retail investors, the return spread between winners and losers starts increasing and becomes highly positive for stocks in the top quantile of retail trading intensity, at 2.78% per month. This table therefore suggests that stocks more intensely traded by retail investors appear to exhibit more price underreaction, consistent with our hypothesis that retail investors contribute to price underreaction through their contrarian trading behavior.

Figure 8 plots the cumulative retail net inflow as a fraction of total market trading volume into winner, median, and loser momentum portfolios for the 24 months prior and the 12 months after portfolio formation. We define net inflow as the difference between purchases and sales by the individual accounts in our sample, after subtracting the full sample average of net inflows to correct for the downward cumulative trend of net purchases in our sample period (Figure 1). This correction allows us to identify abnormal net individual trading as in Kaniel et al. (2012), Grinblatt and Keholajru (2001) and others. Figure 8 shows that the loser momentum portfolio exhibits positive cumulative net inflows that peak in the ten months after portfolio formation, while the winner portfolio exhibits negative cumulative net inflows. The Figure also report the cumulative return for the Hi – Lo portfolio and the long and short leg separately to provide further evidence on the timing and magnitude of the phenomenon,

Figure 9 provides further evidence of the timing of retail net inflow into stocks experiencing earnings surprises. The top panel plots average cumulative return for a window of nine days around the date of the earnings announcement for each of the three groups of stocks classified according to the magnitude of their earnings surprises. For the group in the lowest tercile of earnings surprises, prices fall by about -3% on the date of the announcement and keep declining over the following days, although a much slower pace. For the group in the upper tercile, prices rise by around 3% on the date of the announcement and tend to stay flat. The stocks in the middle tercile experience a slight increase in price on announcement day that tends to reverse in the following days. The bottom panel in Figure 9 shows the cumulative mean daily net inflow into each group of stocks from the investors in our sample during the same window around earnings announcements. This plot shows that the timing of retail net inflow appears to line up well with the timing of stocks' cumulative return upon earnings surprises. Average net inflows are positive for the three groups of stocks before the earnings announcement, indicating that there is no informed trading by these investors, at least at the aggregate level. But on the date of the announcement and in subsequent days, net inflow is clearly contrarian for the stocks in the upper tercile and lower tercile of earnings surprises. Moreover, contrarian trading on stocks with positive earnings surprises is concentrated on the day of the announcement, while it shows an upward drift for the stocks with negative earnings surprises that matches the downward drift in the prices of these stocks. This result is also consistent with the returns on momentum portfolios shown in

Figures 6 and 7, and in Table 9, where momentum appears to be concentrated in the portfolio of loser stocks.

The magnitude of the inflows shown in Figure 5 through Figure 9 appears to be modest relative to total volume. However, we need to account for the fact that while the retail investors in our sample are highly representative of the universe of retail brokerage investors, their assets represent a small fraction of the total assets held by retail investors. The total stock holdings in our sample as of June 2014 were $264 billion, while the Flow of Funds data from the Federal Reserve reports that retail investors overall owned $13,883 billion. Therefore, our sample represents about 1.77% of retail holdings. If the trading of our investors is representative of the overall household sector, the modest inflows relative to total trading volume need to be scaled up by a factor of at least 50 times. Moreover, Figure 10 shows that retail trading is higher for small stocks, where its impact its likely higher, and mega-caps.

Table 10 provides statistical corroboration of the results reported in Figure 5 through Figure 9. It presents regressions of the volume-adjusted net inflow into a stock during the month of formation of the momentum portfolio onto its past lagged 2-12 month return (column 1), the lagged return and its interaction with an indicator variable of whether the stock has experienced an absolute earnings surprise in the last four quarters above its median value (column 2), and the lagged return and its interaction with an indicator variable indicating negative momentum (or a negative lagged return).

Column (1) shows that lagged returns forecast negatively net retail inflows into a stock. However, the magnitude of the coefficient declines and its statistical significance disappears once we control for whether the stock experienced significant earnings surprises, as shown in Column (2). This indicates that earnings surprises, not past returns, are the main driver of the contrarian trading behavior of the individual investors in our sample.

If individual investors with brokerage accounts contribute to price underreaction by trading on the belief that markets overreact to information, one might expect these individuals to learn from the data and eventually realize that their contrarian behavior is not rational and it is contributing to price underreaction. However, this learning is likely to take time for three reasons. First, stock ownership is very dispersed in the data, in the sense that each account holds a very small number of stocks, although collectively the investors own the market. Second, on average these retail investors do not trade often. Third, these investors do not observe the behavior of others. Therefore, each investor individually has only a few data points to learn about the optimality of his own behavior and the plausibility of his own theories of how markets react to information. This in turn might lead to persistence in behavior and a significant impact when we add the aggregate effect of individual behaviors.

VI. Alternative Explanations

An alternative explanation for our results is that the contrarianism we observe is a mechanical result of *stale limit orders* posted by retail investors and then forgotten, and being hit by institutional trade flow following the jump in price generated by the earnings surprise.[5] Figure 11 shows that this is not a concern in our dataset: 34.3% are market orders, filled when they are placed, and an additional 46% are filled within 36 seconds from the time they are place. These statistics are even starker if we weight by dollar amount. In this case, we find that the additional 46% of order that is not executed immediately is fulfilled within 6 seconds. We replicate the results

VII. Retail Investors Trading Around Macroeconomic News

Retail investor trading behavior in response to company news raises the question of whether retail investors also trade in response to the release of macroeconomic news. Zhou (2015) documents active trading behavior on S&P 500 and U.S. Treasuries futures around macroeconomic news announcements, which he attributes to sophisticated investors since professional investors tend to dominate trading in futures markets.

It is plausible that retail investors have views on the effects of macroeconomic variables such as growth, inflation, interest rates, or unemployment on asset classes and that they might trade based on these views when there are news announcements about them. In our sample, we can observe retail holdings and trading on exchange traded funds (ETFs), which provide retail investors with the ability to trade on broad market exposures with the same frequency as individual stocks.

We now examine retail trading in ETFs around macroeconomics news. We focus on eight ETFs that capture broad asset classes, including US equities, global equities, bonds, gold, and

[5] Barber, Odean and Zhu (2009) and Linnainmaa (2010) study the limit and market orders of retail investors.

commodities: SPDR S&P 500 ETF Trust (SPY), Vanguard Dividend Appreciation ETF (VIG), Vanguard Total Bond Market ETF (BND), iShares MSCI EAFE Index Fund (EFA), iShares MSCI Emerging Markets Indx (EEM), Invesco DB US Dollar Index Bullish Fund (UUP), SPDR Gold Shares (GLD) and Invesco DB Commodity Index Tracking Fund (DBC). The list of macroeconomic announcements follows Zhou (2015) and it is highly comprehensive (see Table A2 in the Appendix). It includes announcements of Federal Reserve rate decisions, employment and unemployment news, inflation news, durables and nondurables consumption news, industrial production news, etc.

Figure 12 shows returns on the S&P 500 index and the eight ETFs included in our analysis in a 30-day window around macroeconomic announcement days. Each line in each plot shows returns for positive (green line), neutral (black line), and negative (red line) macroeconomic news. For this figure we sign the impact of macroeconomic news on markets using the S&P 500 index return as a reference. Specifically, we calculate the return on the S&P 500 in the five days after each news announcement (inclusive of the news day) and the return in the prior fifteen days, and subtract one from another. We classify a news announcement as positive, neutral and negative if its associated S&P 500 return differential, or "return reversal," falls into the top, middle and bottom terciles of all return reversals we observe in our sample period. The figure shows that macroeconomic news announcements that have a positive (negative) impact on the US stock market also have a positive (negative) impact on global equity, gold, and commodity markets. By contrast, the impact on the bond market and the U.S. dollar appears to be of the opposite sign. That is, US macroeconomic news announcements that have a positive impact on the US stock market also have a positive impact on global equity markets and commodity markets, and a negative impact on the US bond market and the US dollar. The sign of the impact of macroeconomic news announcements on markets is consistent with the positive correlation of US stock returns with global equity returns commodity returns over this period, and the negative correlation with bond and currency returns.[6]

[6] See Campbell, Shiller, and Viceira (2009), Campbell, Serfaty-de-Medeiros and Viceira (2010), and Campbell, Sunderam, and Viceira (2017).

Figure 13 plots cumulative normalized daily retail net inflow into each ETF from our sample of retail investors over a 30-day window around macroeconomic news announcements.[7] The figure shows evidence of contrarian trading behavior in the most traded equity ETFs around macroeconomic news announcement dates that tends to revert about a week after the announcement. There is no visual evidence of contrarian trading in bond and commodity ETFs.

Table 11 tests for contrarian trading behavior on the day of macroeconomic news announcements for equities and gold. Specifically, we regress net flows into all equity ETFs, SPY (S&P 500) and GLD (gold) onto a dummy variable indicating whether the macroeconomic news announcement is better than prior professional consensus values. The table shows statistically and economically significant evidence of retail contrarian trading behavior on equity ETFs around the announcements. The sign of the news variable in the regression for the gold ETF is also negative, but it is not statistically significant and the size of the coefficient is much smaller than the sign of the coefficient in the equity ETF regressions.

Overall, we find evidence of contrarian retail trading on aggregate equity indexes in response to macroeconomics news announcements, although it is statistically and economically less significant than contrarian trading on individual company stocks in response to company news. It is perhaps surprising that we find any evidence of contrarian trading behavior on macroeconomic news at all, as understanding the implications of macroeconomic news for aggregate indices is significantly more complex than understanding the implications of specific company news such are earnings announcements for individual stock prices.

VIII. 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. We examine retail investor trading behavior around company and macroeconomic news announcements using a database containing the

[7] We define normalized daily retail net inflow into an ETF as retail net purchases of the ETF in a given trading day divided by the lagged 50-day moving average of daily retail trading volume. We calculate daily trading volume as the average of dollar purchases and sales in any given trading day. We calculate cumulative net inflow by accumulating the daily normalized net inflow, relative to the day before the news announcement day, similar to the cumulative return calculation in the event study.

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. There is also weaker evidence that they trade as contrarians after macroeconomic news announcements. The retail investors in our sample exhibit a disposition effect, but this effect cannot explain their contrarian buying behavior, and it doesn't appear to fully explain contrarian selling behavior.

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.

We hypothesize that the brokerage retail investors in our sample might believe that stock prices overreact to news announcements, and trade consistently with this belief. 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.

These results paired with the decline in direct stock ownership by retail investor we document in our sample, suggest that Momentum might become less pronounced over time.

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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.

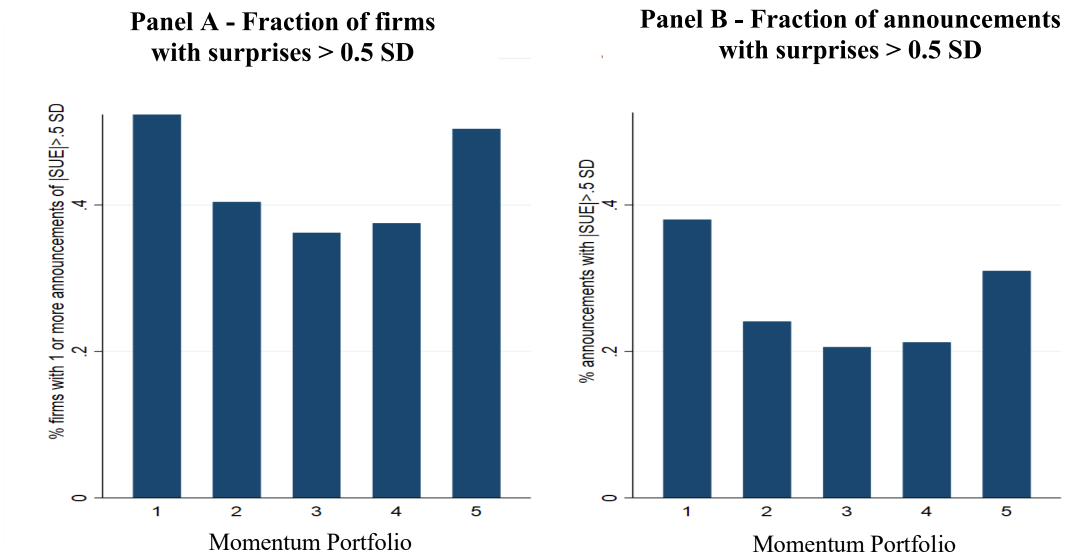


Figure 2. *Retail Inflows into Momentum Portfolios*

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.

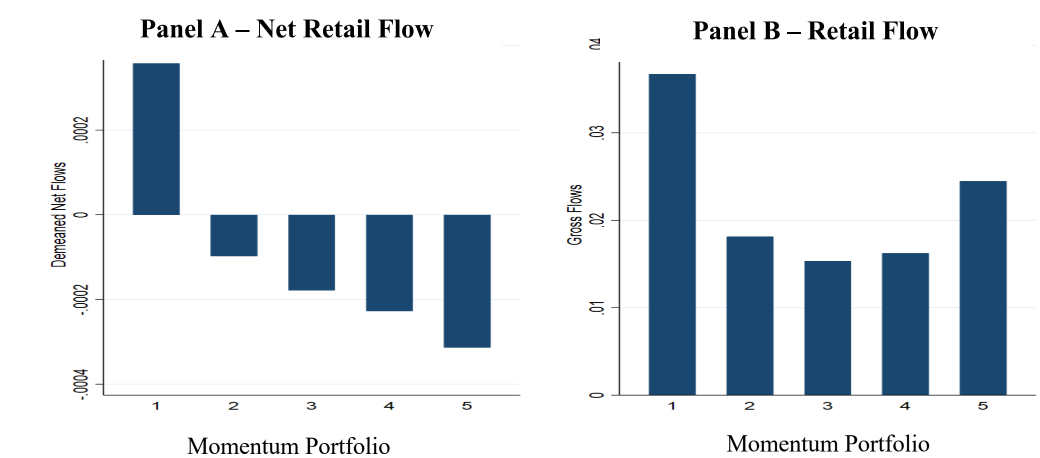
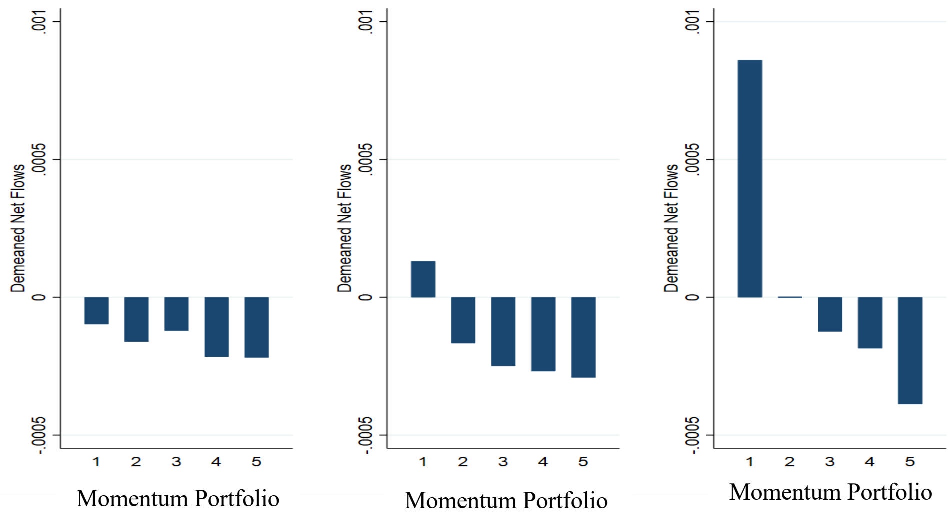


Figure 3. *Retail Net Inflow into Momentum Stocks by Size of the Earnings Surprise*

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 4. *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.

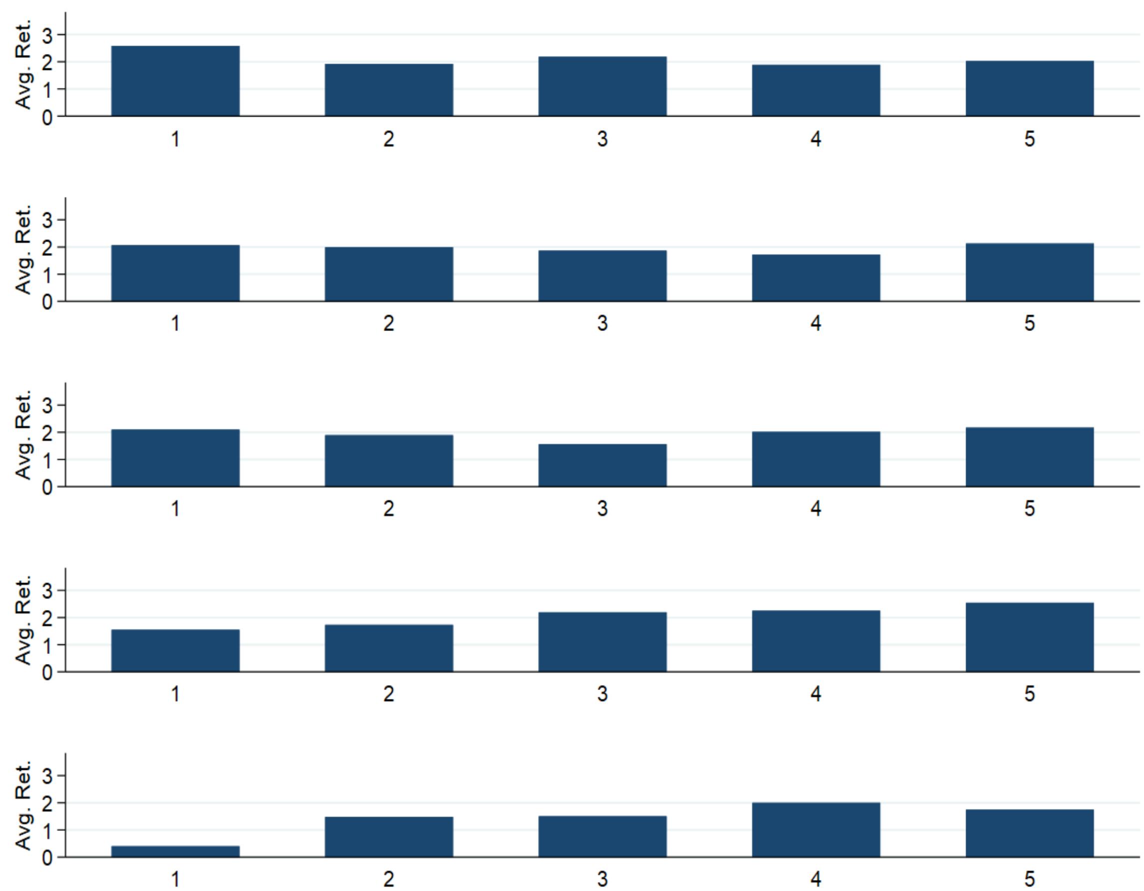
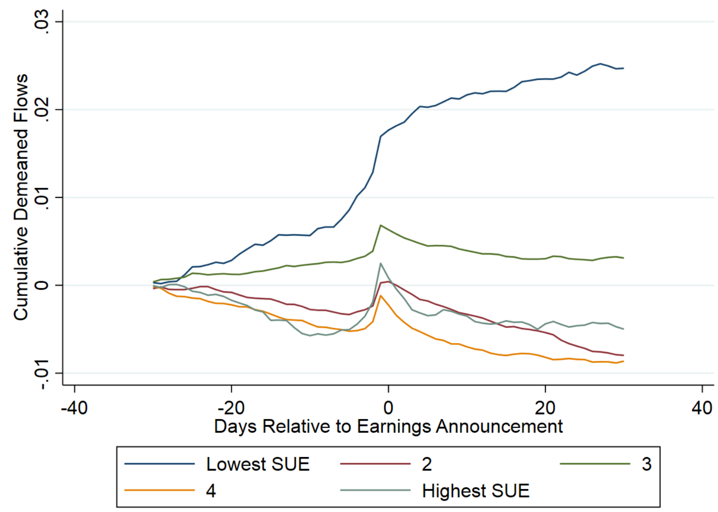


Figure 5. *Daily Net Retail Flows around Earnings Announcements*

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

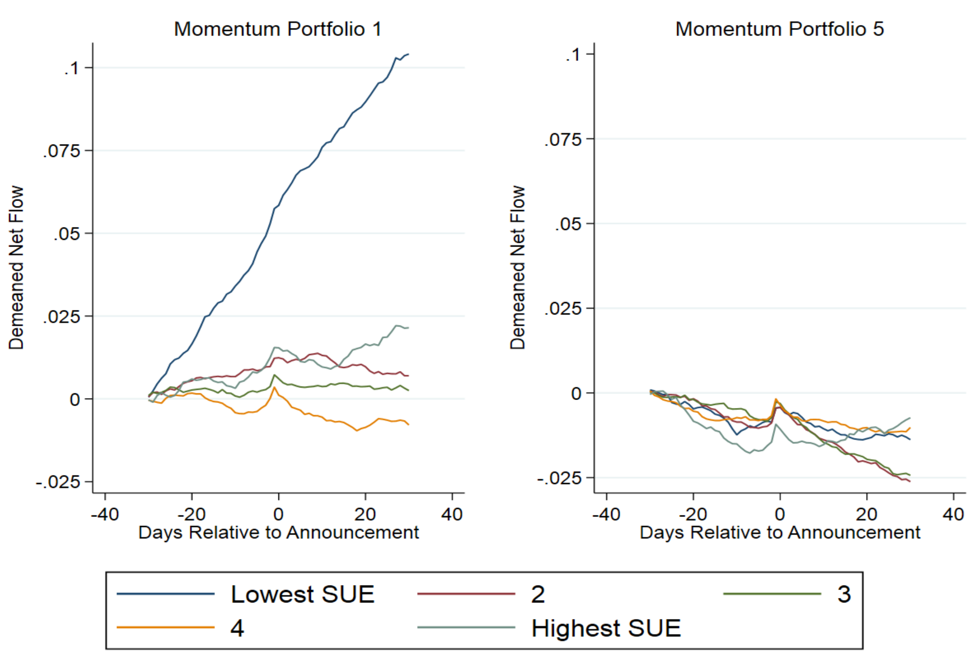
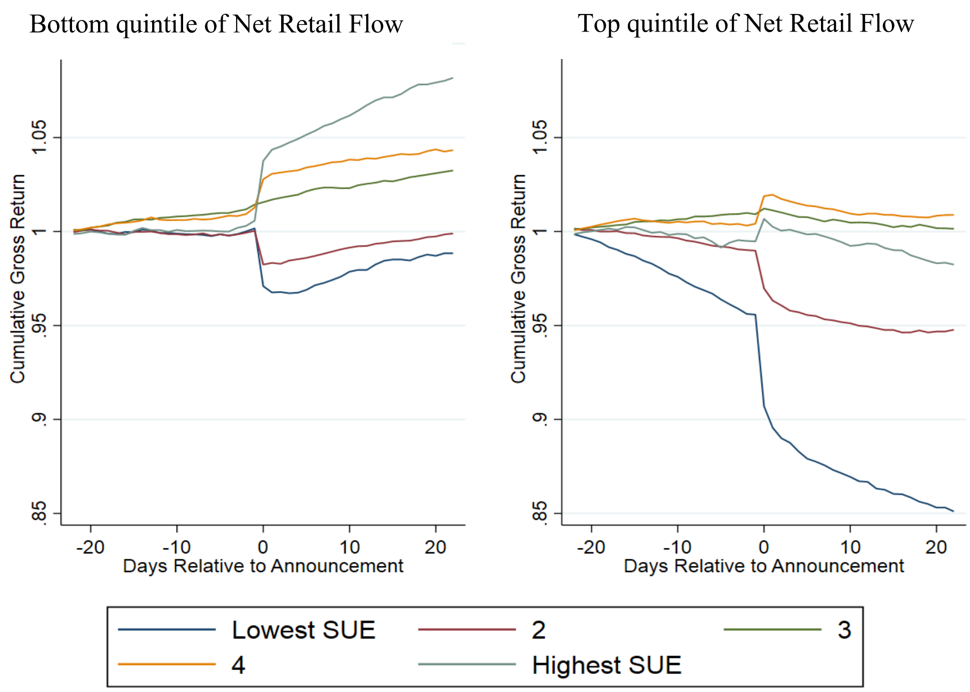


Figure 6. *Cumulative returns by Size of the Earnings Surprise and Net Retail Flows*

Each quarter, we sort firms into 5 groups based on their SUE. Then, within each of these groups, we form 5 subgroups based on the cumulative demeaned net retail flow from t=0 to t=+22. Within each of these subgroups, we calculate the average cumulative market-adjusted return starting at t = -22. The left panel plots the cumulative returns for firms with the biggest retail outflows, while the right panel plots the cumulative returns for firms with the biggest retail inflows. The bottom panel performs the same exercise on the whole dataset, as a check that the results are not due to any idiosyncrasy in the sample.



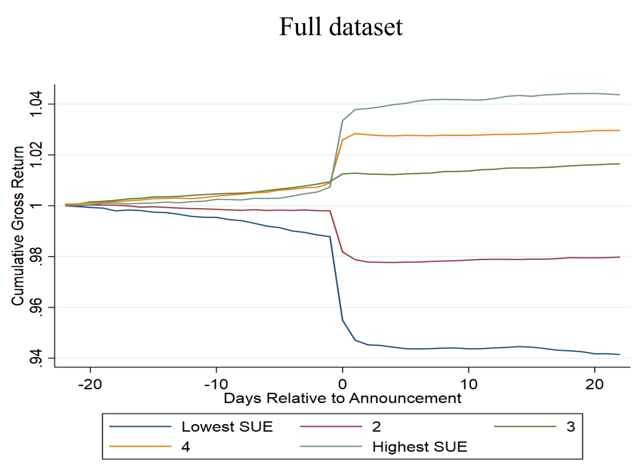
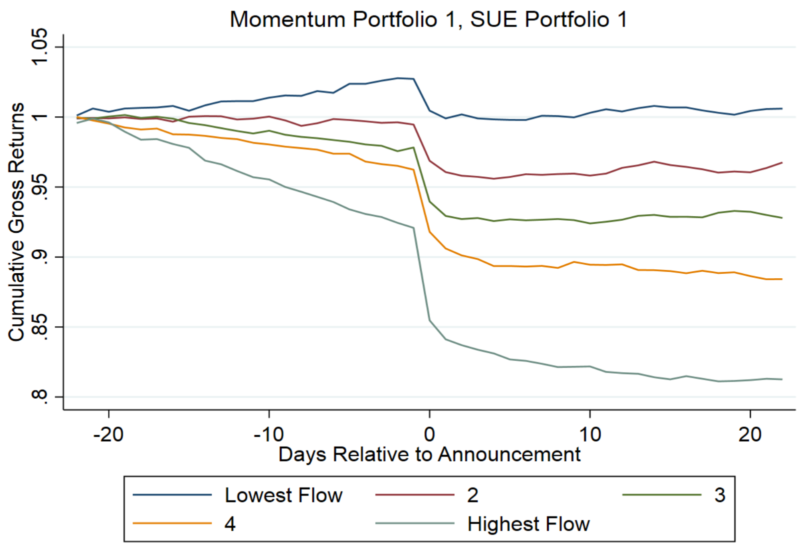
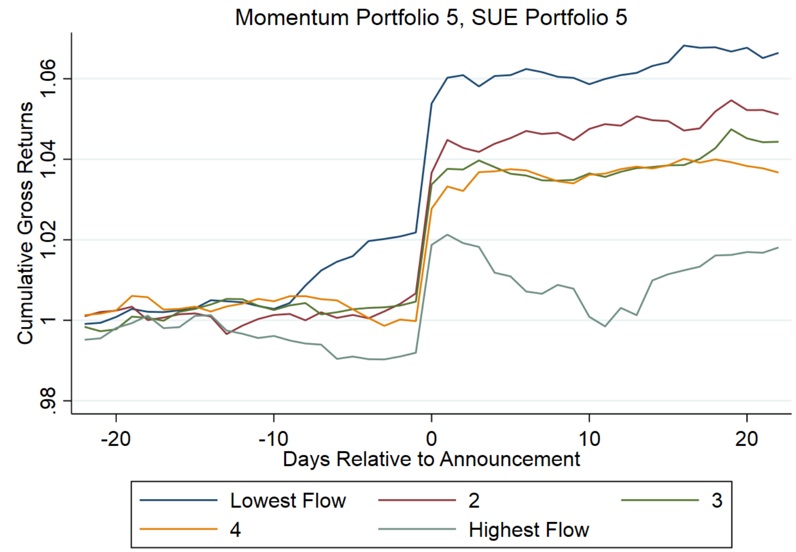


Figure 7. *Cumulative Returns by Momentum Portfolio, Size of the Earnings Surprise and Net Retail Flows*

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.





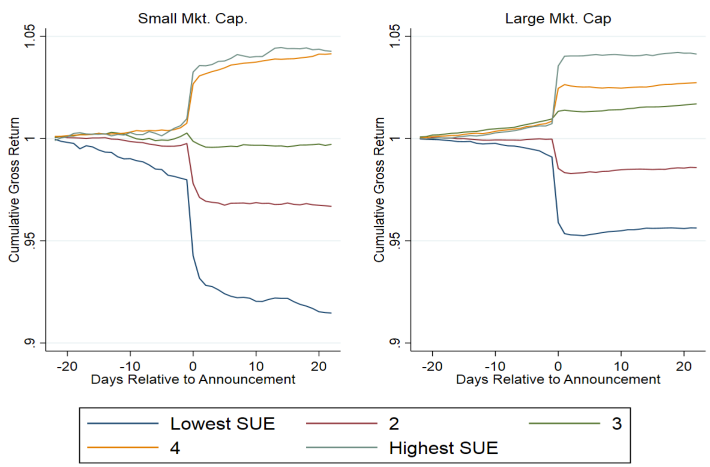
Momentum Portfolio	SUE quintile	Retail flow quintile	Cumulative return from t=0 to t==1	Cumulative return from t=1 to t==22
1	1	1	0.9798	1.0026
1	1	2	0.9749	0.9973
1	1	3	0.9613	0.9859
1	1	4	0.9555	0.9621
1	1	5	0.9299	0.9450

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

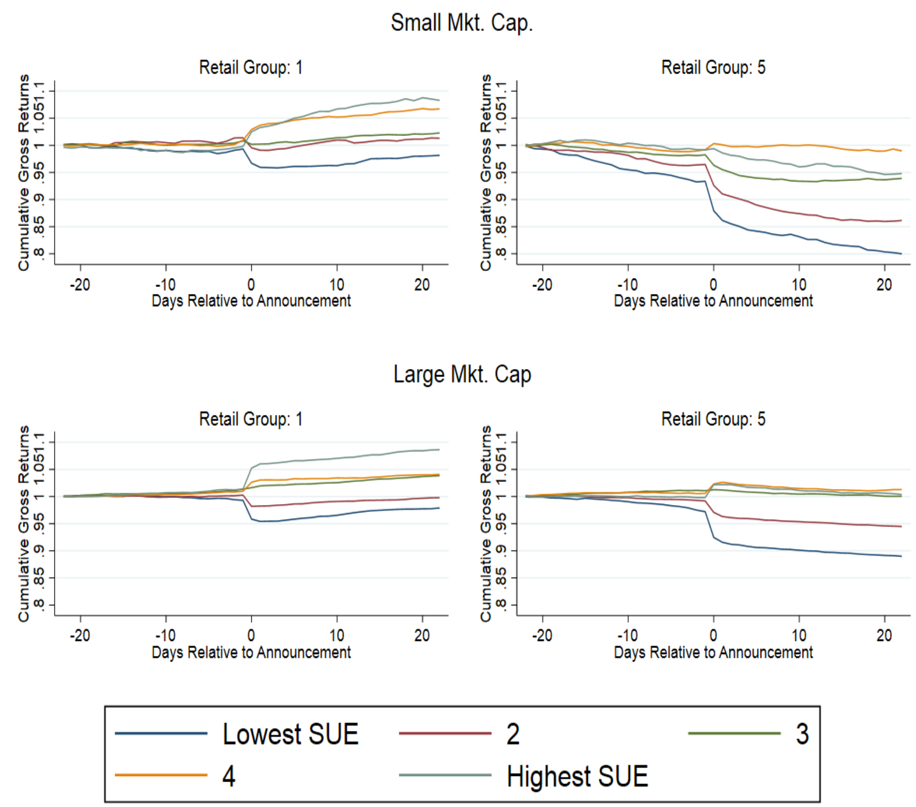


Figure 9. *Cumulative Returns by Momentum Portfolio, Size of the Earnings Surprise, Net Retail Flows and Institutional Ownership*

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.

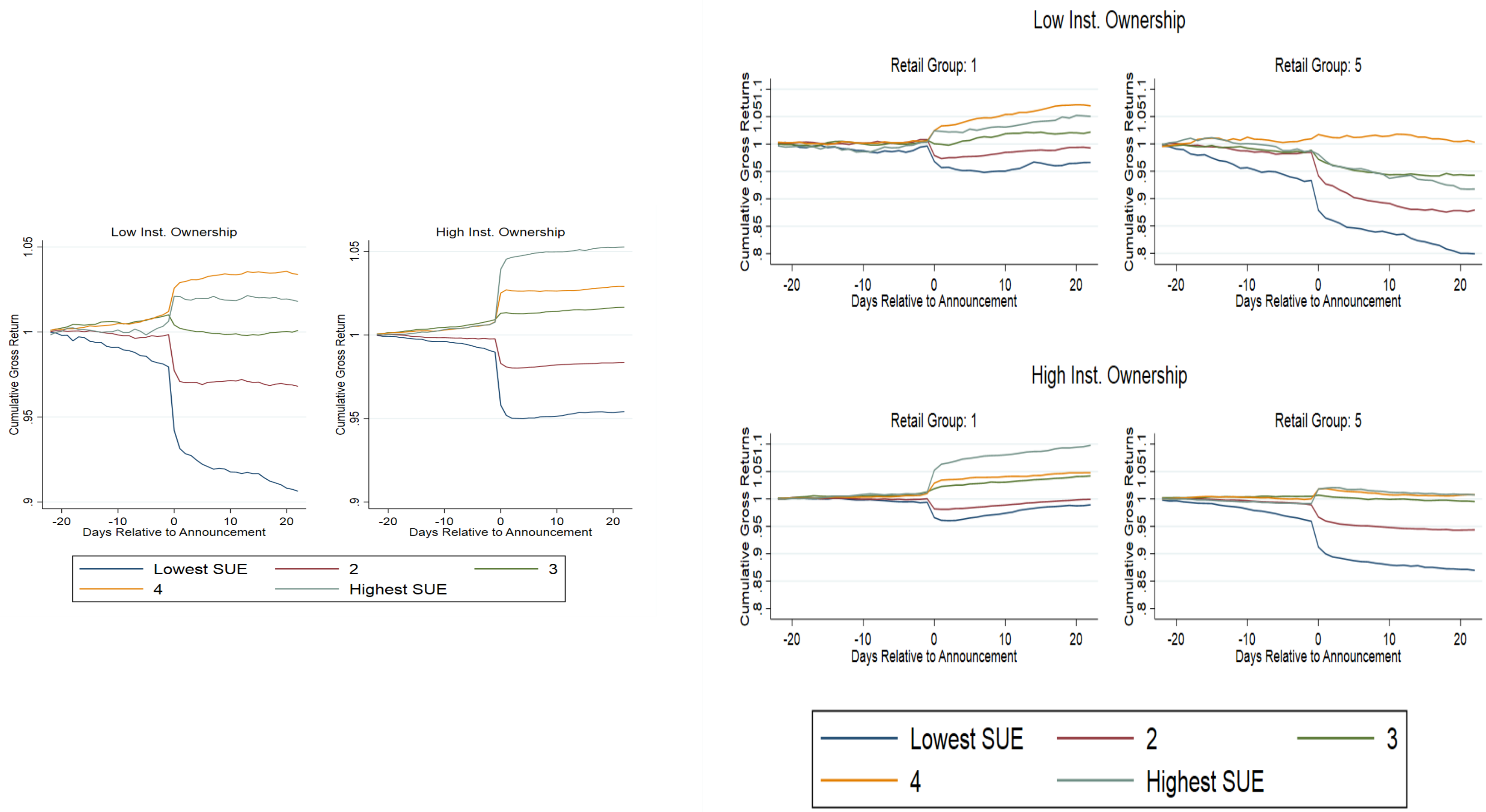


Figure 10. *Fraction of Total Volume captured by our Sample*

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.

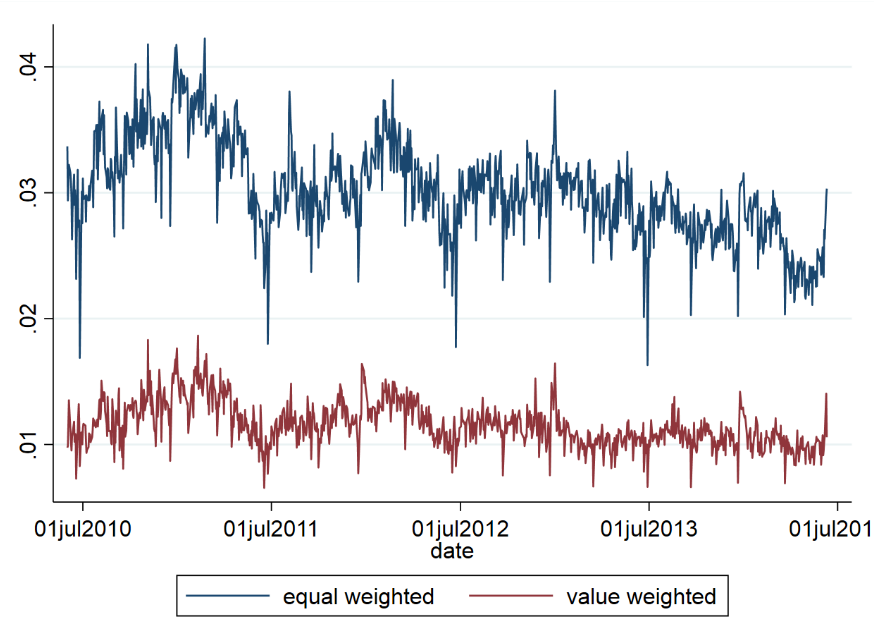
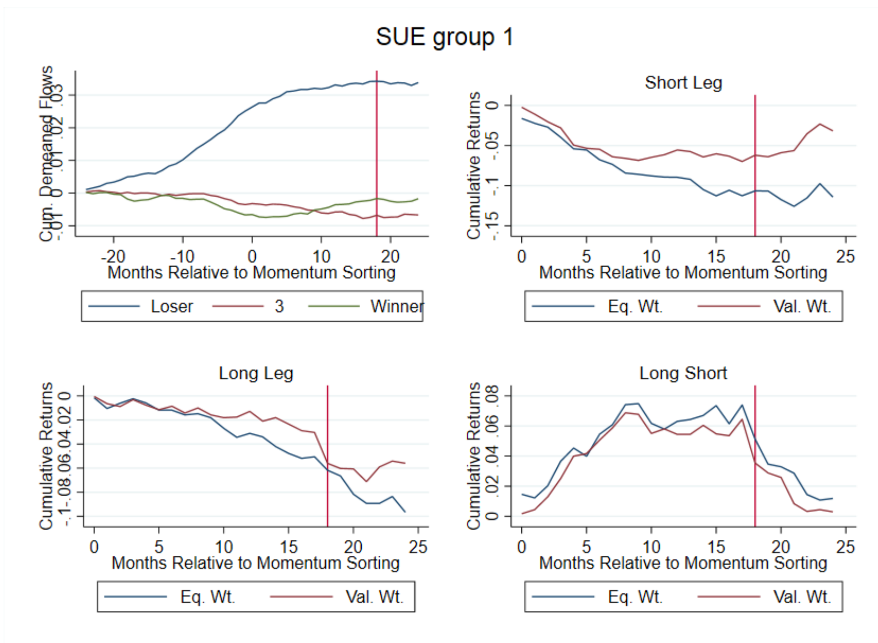


Figure 11. *Cumulative Retail Net Inflow into Momentum Stocks by SUE Group – Longer Horizon*

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

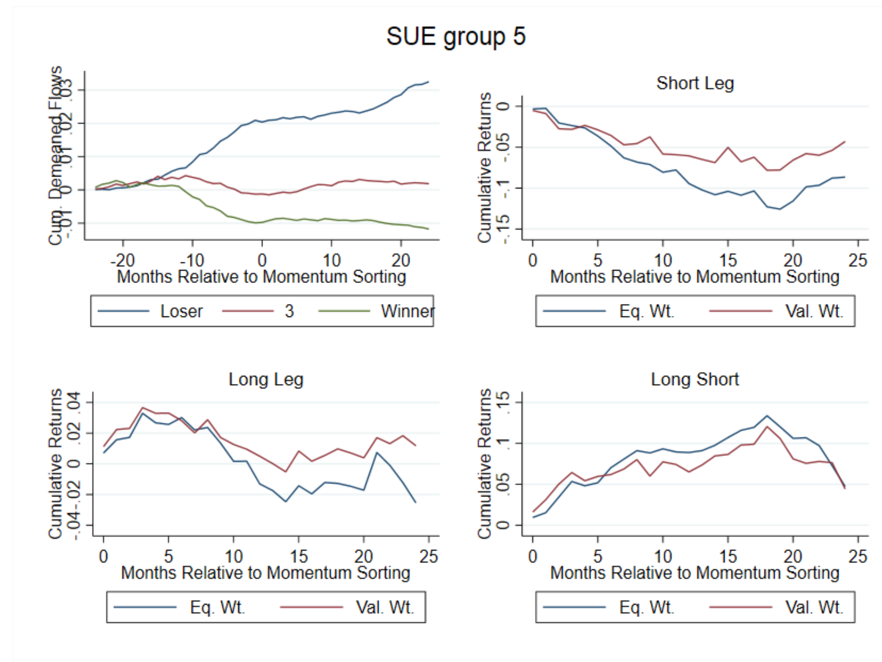


Figure 12. *Longer-run Returns by Momentum, Size of the Earnings Surprise and Net Retail Flows*

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.

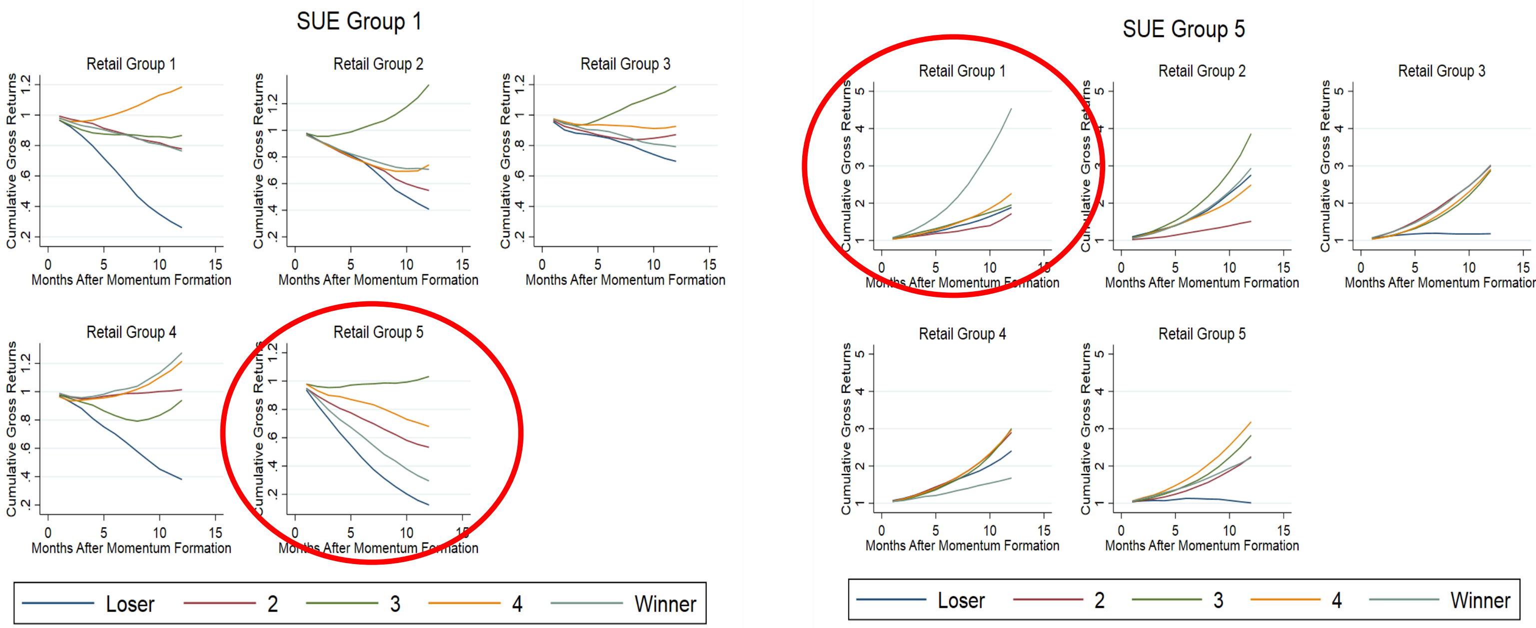


Figure 13. *Retail Contrarian Index*

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.

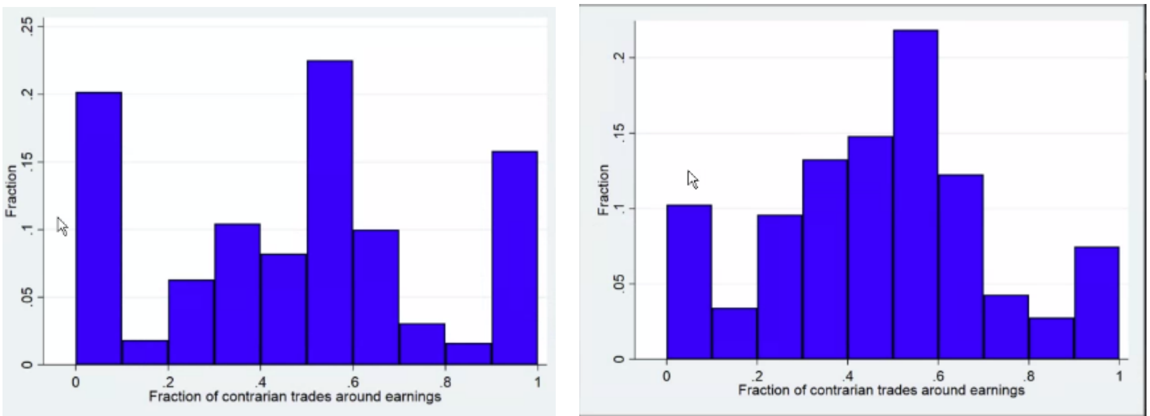


Figure 14. *Limit and Market Orders*

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.

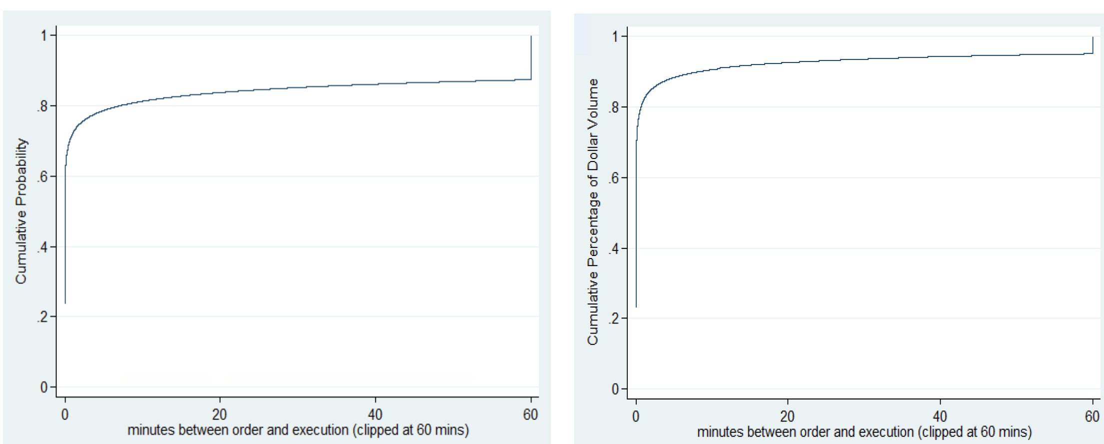
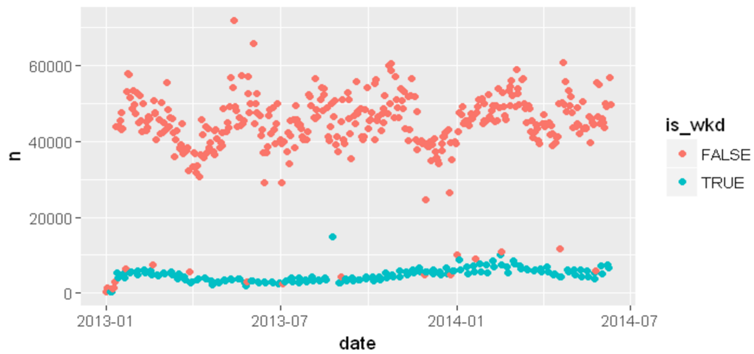


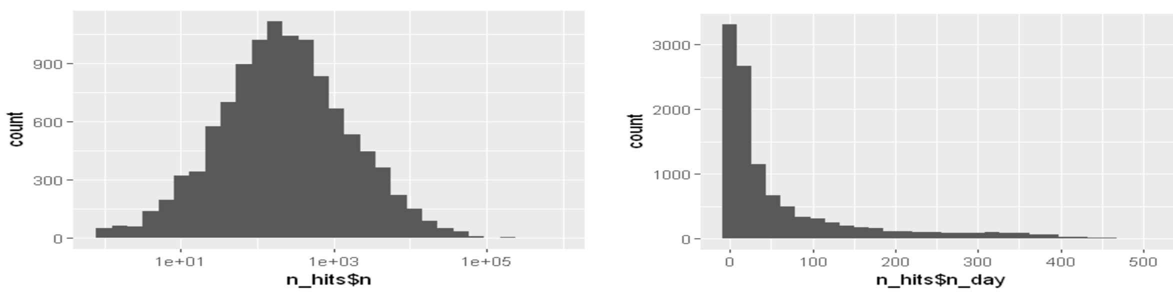
Figure 15. *Attention*

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.

Panel A - Daily number of web-clicks



Panel B - Distribution of Total and Daily Clicks



Panel C - Distribution of Visit Lenght

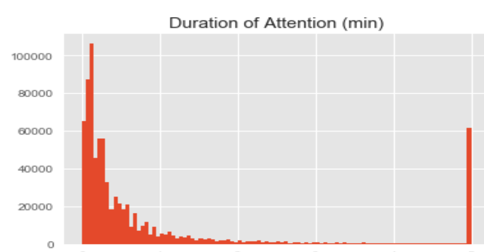


Figure 16a. *Retail ETF Flow around Macroeconomic News: Return*

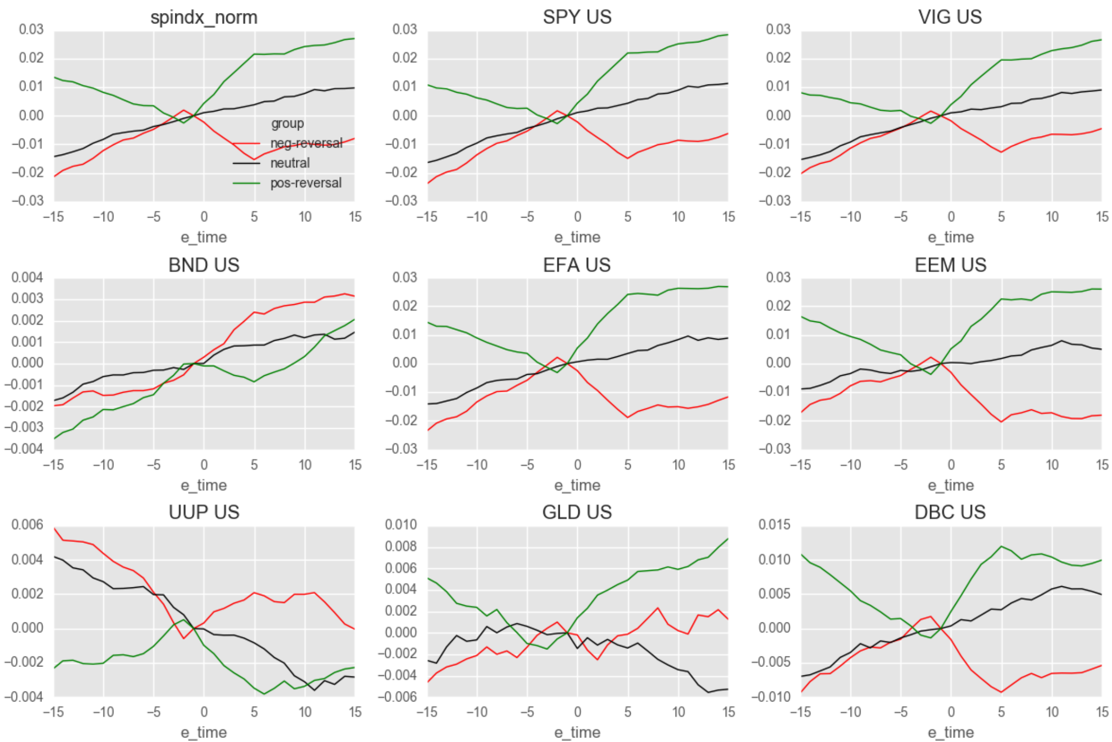


Figure 16b. *Retail ETF Flow around Macroeconomic News: Normalized Net Inflow*

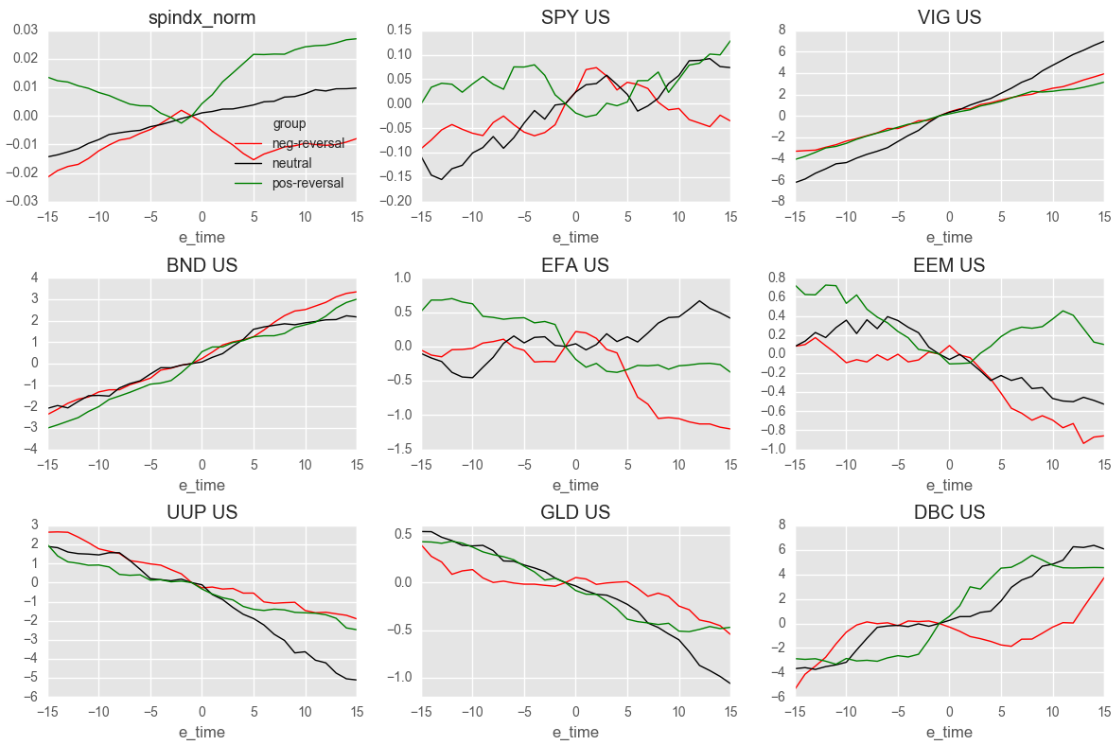


Table 1. *Descriptive Statistics: Account Holdings and Trading Frequency*

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

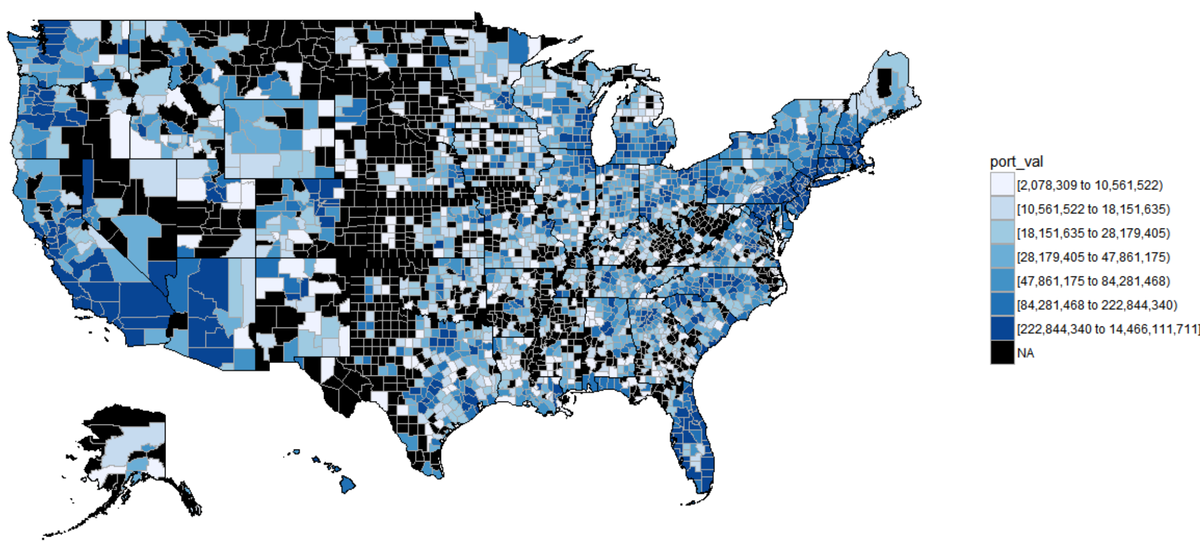


Table 3. *Account-level Factor Regressions: Fama-French 3-Factor Model with Momentum*

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 4. *Contrarian Behavior and Company Earnings*

(A) 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

(B) Realized Gain of Contrarian Trading around Company Earnings

This table reports net gains retail investors realize from contrarian trading around company earnings. For comparison, the table also reports embedded gains of retail investors that do not engage in contrarian trading around earnings and realized gains from trading outside earnings. Mean, median and standard deviation are calculated across account-holding-earnings pairs. Value-weighted mean is based on the dollar size of a stock holding on the last trading day before the earnings.

	Realized or Embedded Gain			
	EW Mean	VW Mean	Median	Std Dev
Earnings: Contrarian Trading	8.36%	5.73%	3.78%	25.51%
Embedded Earnings: No Contrarian Trading	17.15%	17.60%	9.39%	31.21%
Trading outside Earnings				

Table 5. *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 6. *Trading Around Company Earnings*

These tables report summary statistics on retail trading activities around company earnings by earnings surprise (SUE). Panel (A) is percentage based on number of accounts: first 2 columns summarize trading activities during the first five trading days since earnings. Next 3 columns further break out accounts by their trading before earnings for accounts that buy after earnings and last 3 columns for those that sell after earnings. Panel (B) is based on dollar volume. First 3 columns are average percentage of retail volume that are buy, sell and net buy across securities. Last 3 columns are median.

(A) By Number of Accounts

	After Earnings		Among Buy After Earnings			Among Sell After Earnings		
SUE	Buy	Sell	Sell Before	No Trading	Buy Before	Sell Before	No Trading	Buy Before
1-Negative	52.98%	47.02%	0.74%	97.80%	1.46%	1.16%	96.17%	2.68%
2	50.76%	49.24%	0.74%	97.95%	1.30%	0.88%	96.82%	2.31%
3	50.23%	49.77%	0.68%	98.35%	0.97%	0.63%	97.39%	1.99%
4	49.32%	50.68%	0.61%	98.51%	0.88%	0.55%	97.83%	1.62%
5-Postive	49.27%	50.73%	0.47%	98.89%	0.63%	0.65%	97.61%	1.74%

(B) By Trading Volume

	Post Earnings Trading Amount					
	Mean across Securities			Median across Securities		
SUE	Pct. Buy	Pct. Sell	Pct. Net Buy	Pct. Buy	Pct. Sell	Pct. Net Buy
1-Negative	49.4%	50.6%	-1.3%	47.7%	52.3%	-4.7%
2	47.6%	52.4%	-4.8%	37.7%	62.3%	-24.7%
3	47.3%	52.7%	-5.4%	34.0%	66.0%	-32.1%
4	46.0%	54.0%	-8.0%	26.4%	73.6%	-47.2%
5-Postive	45.3%	54.7%	-9.3%	23.6%	76.4%	-52.8%

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

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	Is Sold	Is Sold	Is Bought	Is Bought	Is Bought
	(1)	(2)	(3)	(4)	(5)	(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 8. *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 9. *Momentum Portfolio Returns and Retail Trading*

This table reports monthly returns of conditional momentum portfolios during the sample period from June 2010 to June 2014. The stocks are sorted along market cap, prior return and retail trading activities each month. Then equal-weighted monthly portfolios are constructed along prior return and retail trading dimensions by combining along market cap tertiles.

	Retail Trading				
Prior Return	1-Low	2	3	4	5-High
1-Losers	3.06%	2.85%	1.51%	0.60%	-2.25%
2	2.70%	1.93%	1.35%	0.79%	-0.51%
3	2.72%	1.78%	1.48%	0.92%	0.28%
4	2.33%	2.04%	1.74%	1.44%	0.88%
5-Winners	2.47%	2.24%	2.24%	1.51%	0.53%
5-1	-0.59%	-0.61%	0.73%	0.91%	2.78%

Table 10. *Determinants of Retail Net Purchases: Fama-MacBeth Regressions*

The table reports Fama-MacBeth regressions of retail net inflow on size, valuation ratio, prior stock return and earnings. Dependent variable is normalized retail net inflow, defined as net buy volume divided by total trading volume for a stock during the portfolio formation month. *Lagged BM* is lagged industry-adjusted book to market ratio. *Prior Return* is a stock's prior 12-month return excluding last month. *Is Earning Surprise* is a dummy variable indicating absolute earnings surprise in the last 4 quarters above its median value. *Is Negative Return* is dummy variable indicating negative prior return. p-values based on robust standard errors are reported below estimated parameters.

	Normalized Retail Net Purchases		
	(1)	(2)	(3)
Log(Market Cap)	0.0005	0.0005	0.0005
	p = 0.000***	p = 0.000***	p = 0.000***
Lagged BM	0.0003	0.0003	0.0002
	p = 0.126	p = 0.123	p = 0.115
Prior Return	-0.072	-0.033	-0.076
	p = 0.0003***	p = 0.268	p = 0.00005***
Prior Return x Is Earnings Surprise		-0.075	
		p = 0.048**	
Prior Return x Is Negative Return			-0.043
			p = 0.695
Constant	-0.007	-0.007	-0.007
	p = 0.000***	p = 0.000***	p = 0.000***
Observations	102,802	102,802	102,802
R2	0.004	0.005	0.005

Table 11. *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 (1)	Net Inflow: All (2)	Net Inflow: SPY (3)	Net Inflow: GLD (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. *Account Holdings and Asset Allocation by Age*

(A) Portfolio Value ($) *(B) Stock Allocation*

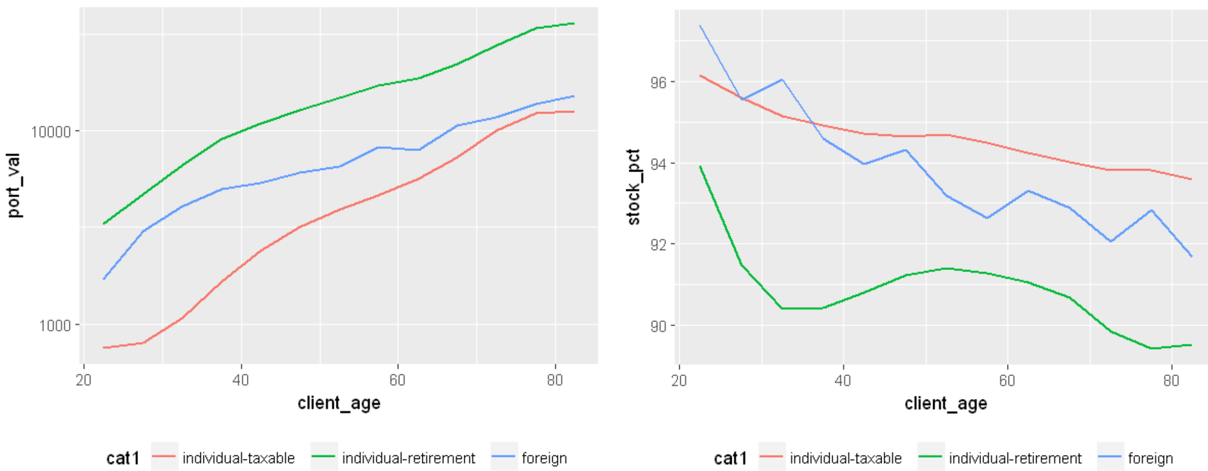
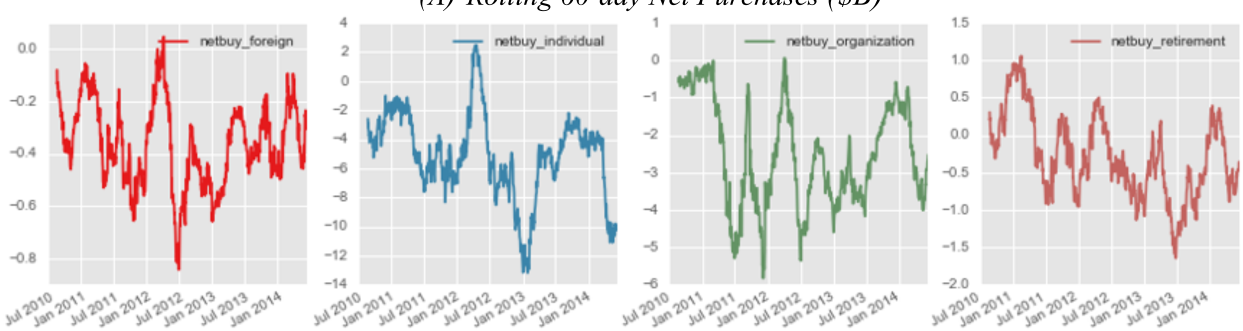


Figure A2. *Aggregate Retail Net Purchases*

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)

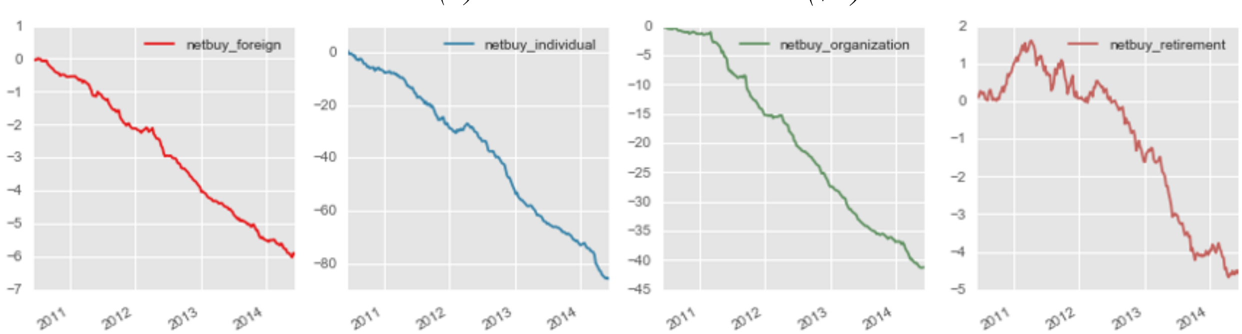


Figure A3. *DGTW Stock Characteristics: by Account Size*

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.

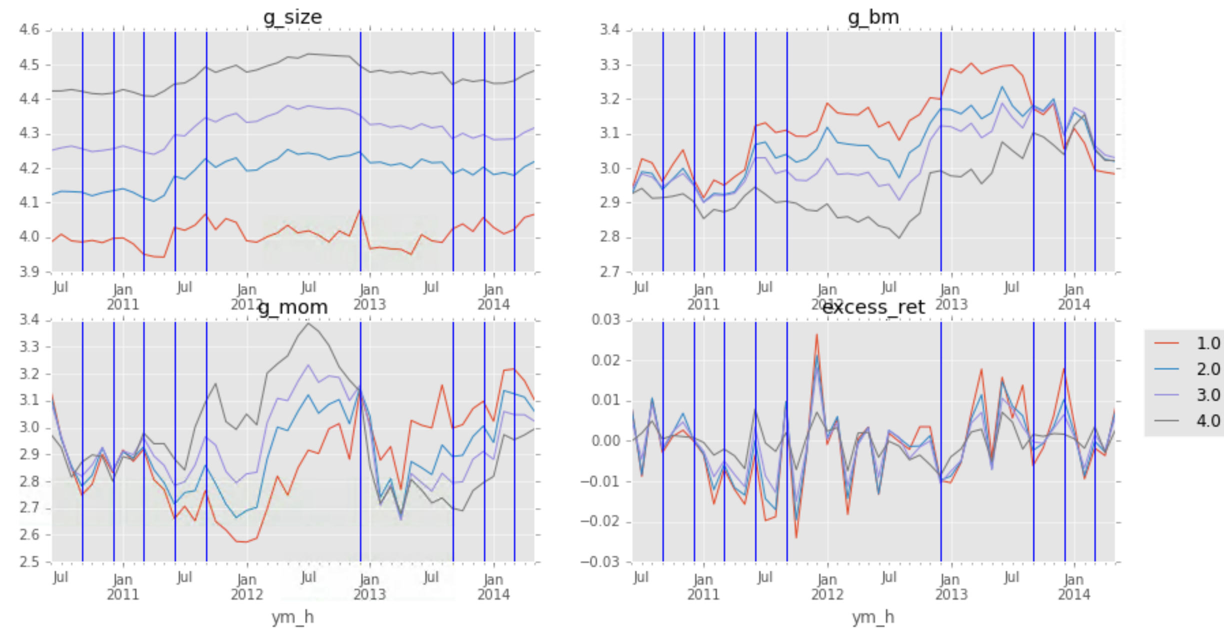


Figure A4. *Retail Trading Around Macroeconomic News*

Top left is net buy for long position and top right is net cover for short position.

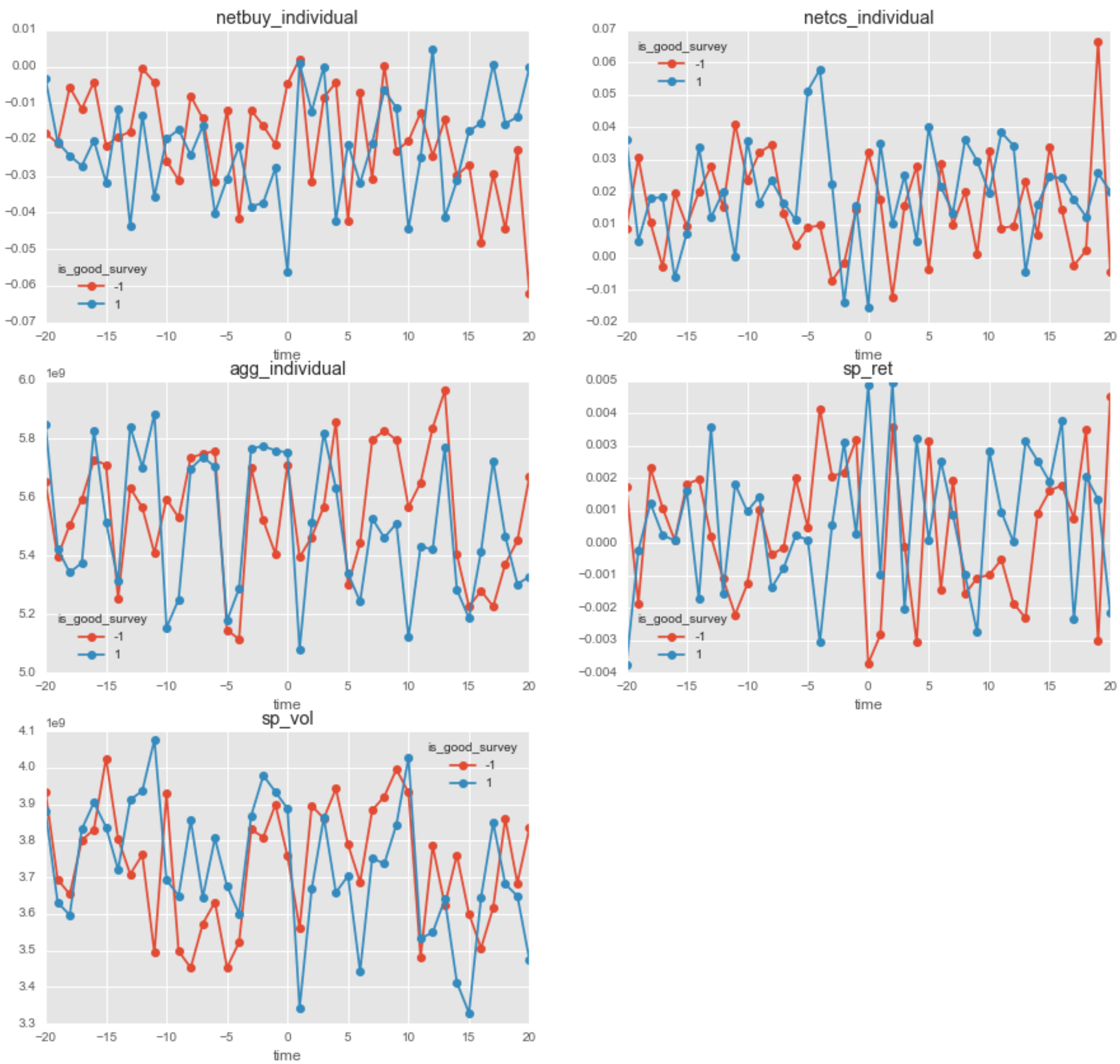


Table A1. *Factor Tilts: 1-way Account Grouping*

(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 A2. *Company Event Types*

The table reports the number and frequency of company events from Capital IQ for the firms in our sample.

Event	Nr of events	% of events
Company Conference Presentations	106,892	13.29%
Announcements of Earnings	82,915	10.31%
Earnings Calls	60,470	7.52%
Earnings Release Date	56,200	6.99%
Product-Related Announcements	50,621	6.30%
Executive/Board Changes - Other	48,489	6.03%
Client Announcements	45,033	5.60%
Dividends	44,773	5.57%
Corporate Guidance - New/Confirmed	42,780	5.32%
Fixed Income Offerings	38,589	4.80%
Buyback Tranche Update	31,970	3.98%
Annual General Meeting	19,929	2.48%
Business Expansions	19,598	2.44%
M&A Transaction Closings	18,859	2.35%
Debt Financing Related	12,649	1.57%
Seeking Acquisitions/Investments	11,802	1.47%
Shelf Registration Filings	11,110	1.38%
Lawsuits & Legal Issues	10,556	1.31%
M&A Transaction Announcements	10,016	1.25%

Table A3. *Macroeconomics News Announcement Type*

The table reports macro news over our sample period from Zhou, J., 2015, "The Good, the Bad, and the Ambiguous: The Aggregate Stock Market Dynamics around Macroeconomic News".

Macro News Type	N	% better-prior	% better-survey
FOMC Rate Decision	30	0.0%	0.0%
Change in Nonfarm Payrolls	49	57.1%	46.9%
Initial Jobless Claims	213	54.9%	53.5%
Consumer Confidence Index	49	49.0%	44.9%
ISM Manufacturing	49	57.1%	63.3%
CPI MoM	49	42.9%	24.5%
Durable Goods Orders	49	57.1%	57.1%
New Home Sales	49	53.1%	49.0%
Retail Sales Advance MoM	49	49.0%	42.9%
Unemployment Rate	49	53.1%	59.2%
Housing Starts	49	46.9%	44.9%
Existing Home Sales	49	44.9%	38.8%
Industrial Production MoM	49	51.0%	42.9%
PPI MoM	44	50.0%	40.9%
Personal Income	49	44.9%	32.7%
Factory Orders	49	46.9%	49.0%
Leading Index	49	46.9%	53.1%
Pending Home Sales MoM	50	44.0%	48.0%
ISM Non-Manf. Composite	49	55.1%	55.1%