ABSTRACT

Title of Dissertation:	ARE INDIVIDUAL INVESTORS INFORMED TRADERS? EVIDENCE FROM THEIR MIMICKING BEHAVIOR
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Evidence from a large stream of research suggests that individual investors are uninformed noise traders, who push equity prices away from fundamentals. Recent studies, however, find that individual investors are sophisticated—their trades contain information about future stock prices. In this study, I shed light on this debate by examining a potential channel through which individual investors become informed: trading disclosures of other market participants. Specifically, I examine whether individual investors exploit the proprietary trading strategies of institutional investors revealed in 13F filings. Using a large sample of retail trades, I find a significant positive association between the order imbalance of retail investors and the first buys of institutional investors around the 13F disclosure deadline, with the positive association concentrated among transient and growth-style institutions. The results suggest that not only do individual investors engage in mimicking trading, but their mimicking behavior is selective. I further find that retail investors' order imbalance predicts future stock returns, with this predictive ability more pronounced in the week around the 13F disclosure deadline, which suggests that individual investors benefit from their selective mimicking trading. Lastly, I find that mimicking trading accelerates the price discovery of upcoming earnings news. Overall, this study enhances our understanding of how individual investors use public disclosures to become informed and contributes to the debate on whether individual investors are informed traders as well as work on the role of SEC disclosures in leveling the informational playing field.

ARE INDIVIDUAL INVESTORS INFORMED TRADERS? EVIDENCE FROM THEIR MIMICKING BEHAVIOR

by

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Dedication

To Betul and Layla

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Chapter 1: Introduction

Traditionally, individual investors have been characterized as uninformed noise traders who push prices away from fundamentals, ignore accounting information, and fixate on technical trends (e.g., Shleifer and Summers, 1990; Barber, Odean, and Zhu, 2009; Blankespoor, deHaan, Wertz, and Zhu, 2019). A recent stream of literature, however, shows that these investors may not be as naïve as previously thought—their trades are informative about future stock prices and earnings (e.g., Kaniel, Liu, Saar, and Titman, 2012; Kelley and Tetlock, 2013). In this study, I shed light on this debate by exploring a unique channel through which individual investors can become informed, namely, by exploiting the proprietary trading strategies of institutional investors revealed in 13F filings.

A rational investor will incorporate an informative signal into her valuations so long as the benefit of doing so outweighs the cost (Grossman and Stiglitz, 1980). Each quarter, SEC-mandated 13F portfolio holdings reports filed by institutional investment managers disclose potentially valuable information.[1] For instance, Daniel, Grinblatt, Titman, and Wermers (1997) show that mutual fund managers can select stocks that outperform the average stock with the same characteristics in the next quarter, and Yan and Zhang (2007) find that trading by transient institutions predicts future earnings surprises and earnings announcement abnormal returns.[2] However, it is not clear whether individual investors exploit these potentially informative signals due to the awareness, acquisition, and integration costs associated with doing so (Blankespoor et

[1] Only institutions with less than $100 million in equity assets under management and holdings with fewer than 10,000 shares or less than $200,000 market value are exempted from this requirement, which needs to be met within the 45 days following the calendar quarter-end.
[2] Extant literature also finds that fund performance declines with the initiation of disclosure (Shi, 2017) and with more frequent disclosure (Agarwal, Mullally, Tang, and Yang, 2015), consistent with institutional portfolio disclosures revealing trade secrets.

al., 2019; Blankespoor, deHaan, and Marinovic, 2020). In this study, I examine the extent to which individuals are able to reap the benefits of publicly available trading disclosures by overcoming these costs.

First, individual investors face information awareness costs: if investors are not aware of trading disclosures or the potential of these disclosures to improve their trading decisions, they will naturally disregard them. However, at least some individual investors access SEC filings through the EDGAR system (Drake, Quinn, and Thornock, 2017). In addition, trading disclosures, especially those from highly visible investment companies, are occasionally covered in the news and on popular websites such as Bloomberg, Forbes, and SeekingAlpha.[3] It is therefore likely that at least some individual investors are aware of these disclosures.

Second, individual investors face information acquisition costs, which refer to the time, effort, and expenses incurred in accessing information. Reading through trading disclosures to identify relevant information may impose significant costs, particularly for resource-constrained individuals. However, news coverage on trading disclosures typically highlights position changes, rather than holdings, which makes the information more readily available. In addition, in recent years subscription-based services such as WhaleWisdom and GuruFocus have started allowing their users to search 13F disclosures, receive notifications of recent filings, and conduct backtests of a given strategy. Thus, as in the case of information awareness costs, information acquisition costs are not likely to be prohibitive for individual investors who seek to benefit from trading disclosures.

[3] See, for example, https://www.bloomberg.com/news/articles/2018-05-11/harvard-endowment-goes-all-in-on-apple-microsoft-and-google, https://www.forbes.com/sites/martinsosnoff/2019/02/20/13f-filings-flashing-yellow-is-buffett-now-a-gunslinger/, and https://seekingalpha.com/article/4249400-hedge-funds-quietly-buying-visa-stock-why ; links all accessed in March 2020.

The third type of information cost that investors must overcome to fully utilize new information entails integration costs, which refer to costs related to evaluating and incorporating new information into their valuation models and trading decisions (Blankespoor et al., 2020).[4] If an individual is uninformed, she may choose to blindly mimic the actions of more sophisticated investors in an effort to rely on their research.[5] In practice, these individuals are likely to follow a random subset of such trades or to select the traders they follow using naïve heuristics. In contrast, an informed individual is likely to conduct her own research and screening on disclosed trades in an effort to identify the most profitable ones.[6] However, it is not clear whether individuals possess sufficient skill and resources to identify the most profitable trades from trading disclosures, even when they attempt to do so. In this paper I seek to provide evidence on whether individuals mimic sophisticated traders, and if so, how successful they are at this task.

Using 13F filings to identify institutional trades and following the novel methodology introduced by Boehmer et al. (2019) to identify a large sample of retail trades from the Trade and Quote (TAQ) database, I examine the relation between retail order imbalance and disclosed purchases of institutions over three windows (three days, one week, and two weeks) around the 13F deadline (i.e., day 45 of the quarter) in a sample spanning the period 2007 to 2017.[7] I find a positive association between institutional first buys and retail order imbalance, which suggests that individuals follow the first buys (i.e., new position initiations) of institutional investors, and more

[4] Earlier analytical work refers to integration costs as "interpretation costs" (Indjejikian, 1991).
[5] This type of blind mimicry is predicted by the theory of informational cascades. As Hirshleifer and Teoh (2003) explain, "An individual is said to be in an informational cascade if, based upon his observation of others (e.g., their actions, outcomes, or words), his selected action does not depend on his private information signal."
[6] This type of sophisticated screening is predicted by the mosaic theory of financial analysis (CFA, 2014; Cheynel and Levine, 2015).
[7] Boehmer et al.'s (2019) approach has been used in recent studies such as Blankespoor, deHaan, and Zhu (2018), Blankespoor et al. (2019), and Farrell, Green, Jame, and Markov (2018). Boehmer et al. (2019) predict that their approach picks up a majority of individual investor trades, as it exploits the fact that retail order flow, but not institutional order flow, observes price improvement in the U.S. I discuss this methodology in more detail in Section 3.1.

importantly, that trading disclosures represent a part of individual investors' information set.[8] This finding is economically significant—an increase from the first quartile to the third quartile in purchases by institutional investors is associated with a 52% increase in retail order imbalance, relative to the sample mean.

To shed light on the types of sophisticated investors that individual investors mimic, I employ cross-sectional analyses. If individuals mimic the trades of the most sophisticated traders whose investment horizon is similar to theirs, they are more likely to profit from these trades. I find that individual investors mimic the trades of transient institutions but not the trades of dedicated or quasi-indexing institutions. When I focus attention on hedge funds, which are typically considered the most sophisticated institutions (e.g., Kosowski, Naik, and Teo, 2007), I obtain similar results: individuals only follow transient hedge funds. These findings are consistent with evidence from prior studies that individual investors and transient institutions tend to have a similar investment horizon, as indicated by their higher portfolio turnover (Barber and Odean, 2000; Bushee, 2001). Individuals also prefer to mimic growth-style funds, which are characterized by holdings of riskier stocks with high historical and expected growth. The intrinsic value of these stocks is harder to assess (Yan and Zhang, 2007), and thus individuals appear to benefit from exploiting the research of their institutional counterparts that have more resources.

Individual investors' selective mimicry of growth-style and transient institutions, which are considered more informed over short horizons (e.g., Ke and Petroni, 2004; Yan and Zhang, 2007), together with their own short-term focus suggests that individual investors are relatively sophisticated in their exploitation of trading disclosures. However, given 13F filings arrive with

[8] In a long portfolio, purchases are more likely to be informative than sales as the choice of stock to sell out of a limited set conveys less information (Chan and Lakonishok, 1993). First buys are also more informative signals than other position increases (Baker, Litov, Wachter, and Wurgler, 2010).

considerable delay (around 45 days on average), it is not clear whether individuals are able to profit from the mimicry of institutions that may have already turned over a significant portion of their positions. Further, as mosaic theory suggests, in integrating the new information with their private information, individual investors may employ idiosyncratic assumptions in interpreting the disclosed trades, or they may apply additional screens on their choice of institutions or positions to mimic.[9] In sum, ex ante it is not clear whether individuals benefit from their mimicking activities.

To address this question, I examine the predictive ability of individual investors' trades around 13F disclosures for future stock returns. Consistent with recent literature (e.g., Kaniel et al., 2012; Kelley and Tetlock, 2013), I find a strong positive relation between net trading by individual investors and subsequent stock returns. More importantly, I find that the predictive ability of individual investors' trades increases significantly in the week around the 13F disclosure deadline.[10] This effect is economically meaningful: the relation between net trading by individual investors and future returns is 6.3% larger during the 13F disclosure week than other weeks of the quarter. This finding suggests that individual investors display some skill in interpreting 13F filings.

Next, I shift focus to the market effects of individual investor mimicking. I first examine whether retail trading around 13F disclosure periods accelerates the price discovery of upcoming earnings news. As trades of short-term institutions predict future earnings surprises (Yan and Zhang, 2007), I expect heavy individual mimetic trading to impound some of the information revealed in the earnings. Consistent with this expectation, I find that the earnings response

[9] Kandel and Pearson (1995) argue that different agents interpret public signals differently as they disagree about the probabilities of events even when they possess identical information.
[10] This period includes 45% of the 13F filings and 68% of the dollar volume of first buys in the calendar quarter.

coefficient (ERC) is lower when retail order imbalance around the 13F deadline week is higher. I also directly examine the price adjustment after 13F filings themselves. Defined as the fraction of future 60-day returns realized in the 5-day period around the 13F deadline, price adjustment is quicker when retail order imbalance in the 5-day period is in the highest tercile compared with the lowest. Overall, retail activity around trading disclosures appears to aid market efficiency.

The individual investor mimicking behavior that I document above may be alternatively explained by delayed reactions to reported earnings, which the trades of transient informed institutions in the previous quarter successfully predict. If this alternative story holds, retail trades may be spuriously correlated with institutional first buys. I address this possibility in two ways. First, I restrict the sample to those stock-quarters in which earnings are reported *after* the 13F deadline window and I control for the previous quarter's earnings news. Second, when examining stock-quarters in which earnings are reported *before* the 13F deadline window, I control for both current- and previous-quarter earnings news. The results remain qualitatively unchanged in both specifications, suggesting that inferences are robust to considering this alternative explanation.

I conduct several sets of robustness tests to strengthen my inferences. I find that the results are robust to (i) measuring institutional first buys based on the number of institutions buying, rather than using the volume-based measure, (ii) expanding the 13F disclosure window to the full quarter, (iii) excluding the financial crisis period, (iv) excluding stock-quarters in which there are no institutional first buys, and (v) including observations with a major information event in heavy-disclosure periods. In addition, placebo tests show that the timing of first buys and retail trading needs to be in sync for the results to hold, that is, my results are not driven by lead-lag relationships caused by an extraneous variable. Specifically, I find no relation between (i) 13F deadline week first buys and retail trading *before* the deadline week, and (ii) institutional buys revealed in the *next* quarter's deadline week and retail trading in the current quarter's deadline week.

Finally, to better understand the mimicking phenomenon, I conduct several additional analyses. First, I examine whether individuals mimic institutional *last sells*. While choosing a stock to sell out of the limited set of stocks already in the individual's portfolio is considered an easier problem than choosing a stock to buy from the universe of stocks, individual investors may still benefit from skillfully examining institutional trades. Consistent with this view, I find that institutional last sells are also mimicked by individuals. Second, I expand trading disclosures to include purchases by corporate insiders and find that individuals also follow insiders in purchasing stocks. To examine the sophistication of individuals' mimicry of insiders, I follow Cohen, Malloy, and Pomorski (2012) and classify insider trades into "routine" versus "opportunistic" trades based on the timing and frequency of their purchases. In line with sophisticated screening, I find that individuals do not mimic routine trades but do mimic opportunistic local insiders' trades, which are informative about future returns (Cohen et al., 2012).

My empirical setting has strengths and limitations. On the strengths side, using TAQ data and Boehmer et al.'s (2019) recent methodology enables me to identify a large portion of individual trades. Indeed, to the best of my knowledge, no other method or data set allows researchers to identify a broader set of individual investor trades. However, I do not have access to individual investors' nonmarketable limit orders or orders fulfilled on an exchange, and thus the data still have a considerable type II error rate. On the other hand, as Boehmer et al. (2019) note, their approach is conservative and designed to produce a low type I error rate (see also Blankespoor et al., 2019). Another limitation of my study is that I only identify individuals' trades, not their holdings, and do not have information on their transaction costs. Thus, I cannot conclusively establish whether these investors realize an economic profit from their mimicking behavior. In addition, I do not claim that all individual investors act as sophisticated traders. Notwithstanding, I am able to show that at least some individual investors act in a sophisticated manner when exploiting trading disclosures.

This paper contributes to several literatures. First, it contributes to the literature that examines individual investors' naiveté versus sophistication. While earlier studies using samples before 2000 characterize individuals as uninformed noise traders (e.g., Hvidkjaer, 2008; Barber, Odean, and Zhu, 2009), recent studies find evidence of informed trading by the group (e.g., Kaniel et al., 2012; Kelley and Tetlock, 2013). Using the largest sample retail trading volume employed to date (over $26 trillion), I add to this recent stream of the literature by providing evidence that individual investors engage in sophisticated screening of 13F institutions' trading disclosures, which helps explain prior evidence of their informed trading.

Second, this study adds to the growing literature on how individual investors become informed. Prior research shows that in addition to traditional sources such as firm filings (e.g., 10Ks) and analyst reports, individual investors rely on brand visibility (Frieder and Subrahmanyam, 2005), crowdsourced investment research (Farrell et al., 2018), and firm news (Akbas and Subasi, 2019) to improve their decision-making. I add to this work by showing that individuals also exploit, and benefit from, the trading disclosures of sophisticated market participants. Thus, in line with the SEC's focus on facilitating informed decision-making (SEC, 2018), trading disclosures appear to help level the informational playing field.

Finally, this paper contributes to the literature on investor mimicry of others' trades. Frank, Poterba, Shackelford, and Shoven (2004) construct hypothetical mimicking portfolios and show that mimicking strategies can be profitable. Phillips, Pukthuanthong, and Rau (2014), however, find little evidence of skillful trade imitation among institutional investors. In more recent work, Lesmond and Stein (2018) show that while most imitators underperform, some managers appear to be "smart imitators." I add to this literature by showing that at least some individual investors also engage in successful mimetic trading.

The rest of the paper is organized as follows. Section 2 provides a brief review of related literature and develops the paper's testable hypotheses. Section 3 describes the sample, variables, and research design. Section 4 presents the empirical results. Section 5 concludes.

Chapter 2: Related Literature and Hypothesis Development

2.1 Related literature

2.1.1. Individual Investors

Early studies (e.g., Kyle, 1985; Black, 1986) describe traders who irrationally act on noise as if it were value-relevant information, labeling them as "noise traders". Beginning with Shleifer and Summers (1990), individual investors have been regarded as prime candidates for being members of the said group, due to various behavioral biases that hurt their performance. For example, they hold onto their losses (Odean, 1998), trade aggressively (Barber and Odean, 2000), diversify naively (Lewellen et al., 1974; Benartzi and Thaler, 2001) and view trading as entertainment (Dorn and Sengmueller, 2009) and gambling (Dorn et al., 2014). Further, they overweight past performance due to representativeness heuristic (e.g., Barberis, Shleifer, and Vishny, 1998) and favor attention-grabbing stocks (Barber and Odean, 2008).

However, recent evidence suggests some informed trading behavior by the same group. Individual investors' trades predict earnings surprises (Kelley and Tetlock, 2013), stock returns around earnings announcements (Kaniel et al., 2012), and stock returns more generally, up to 12 weeks (Boehmer et al., 2019). Akbas and Subasi (2019) find a strengthened relationship between retail order imbalance and stock returns on positive news days, which they interpret as individuals having news processing skills. Farrell et al. (2018) show a similar heightened relationship on the days crowdsourced research articles come out. The latter two studies offer us some perspective on the information sources individuals seem to utilize. Not surprisingly, they are influenced by traditional sources such as financial statements and analyst recommendations as well (Nagy and

Obenberger, 1994). Frieder and Subrahmanyam (2005) show that individual investors prefer stocks with high brand visibility, likely because they have higher precision information about them. Overall, we still know little about how individual investors gather the information mosaic they use to get informed. My study shows that trading disclosures by other market participants might play an important role in that mosaic.

2.1.2. Sophistication of institutional investors

Institutional investors are professional investors, a group that includes mutual funds, hedge funds, banks, insurance companies, pension funds, and university endowments, among others. Extant literature typically characterizes institutional investors as sophisticated traders, earning positive pre-expense returns (e.g., Grinblatt and Titman, 1993; Daniel et al., 1997; Chen et al., 2000; Wermers, 2000). However, there is significant heterogeneity in their performance. Hedge funds are considered the most skillful (e.g., Kosowski, Naik and Teo, 2007; Rhinesmith, 2015), but there is debate over whether their high fees are justified (e.g., Griffin and Xu, 2009). Research on mutual funds also points to some skill and stock selection ability (e.g., Baker et al., 2010; Berk and Binsbergen, 2015). There is evidence of success by investment companies such as Berkshire Hathaway as well (Frazzini, Kabiller and Pedersen, 2018). More importantly, overwhelming majority of studies on institutional performance show large cross-sectional differences in skill.[11] These findings suggest both a challenge and opportunity for individual investors that seek to benefit from institutional trades. If they possess screening skills, they have the potential to identify the most profitable funds/stocks and thereby exploit proprietary trading strategies revealed in the trading disclosures.

[11] See Fung and Hsieh (2013) and Elton and Gruber (2013) for reviews of hedge fund and mutual fund performance, respectively.

2.2 Hypothesis Development

As discussed earlier, individuals willing to exploit the information revealed in trading disclosures incur awareness, acquisition, and integration costs, collectively referred to as information costs (Blankespoor et al., 2019) or disclosure processing costs (Blankespoor et al., 2020). Assuming they are rational traders, they will seek to incorporate the signals from the disclosures into their valuation models only if their perceived benefit exceeds the information costs. For at least a segment of individual investors, it is likely that this condition is met. Consistent with this expectation, subscription-based services focusing on institutional trading disclosures (e.g., WhaleWisdom, GuruFocus) entered the investment research market in recent years. Based on the prior discussion, I expect that individual investors mimic trades of institutional investors. I present my first hypothesis in the alternative form:

H1: Individual investors mimic trades of institutional investors.

If individuals do engage in mimicking, a natural follow-up question is whether they benefit from doing so. Prior literature examining sophisticated traders find significant heterogeneity among the group. They differ with respect to their investment horizons, investment style, informedness, and risk profiles, among other dimensions. If individuals mimic trades of the most sophisticated traders whose investment horizons are similar to theirs, they should fare better. In that vein, I expect individuals to mimic transient institutions more than dedicated and quasi-indexers as the first group has similar investment horizon to the individuals—both groups turn their portfolios over quickly (Barber and Odean, 2000; Bushee, 2001). Also, extant evidence shows that transient institutions are more informed than other institutions, especially over short horizons (e.g., Ke and Petroni, 2004; Ke and Ramalingegowda, 2005; Yan and Zhang, 2007). Thus, I expect individuals to mimic transient institutions more than others. Similarly, I expect their mimicry of the growth-style institutions to be higher as this group of investors typically hold riskier stocks with high historical and expected growth for which intrinsic value is known to be harder to assess (Yan and Zhang, 2007) and individuals likely try to benefit from the research of their institutional counterparts with more resources. Further, growth-style funds are also more informed in the short term (Chen et al., 2000). Finally, at the stock-level, I expect individual investors to mimic sophisticated traders' purchases of riskier stocks, about which they are likely to be less informed and to rely more on the research and expertise of institutional investors. Based on the discussion above, I state my second hypothesis and its first sub-hypothesis below:

H2: Individual investors benefit from their mimicking of institutional investors.

H2a: Individual investors mimic trades of transient and growth-style institutions and riskier stocks more than others.

Another way to tackle the question of whether individual investors benefit from their mimicking of institutional investors' trades is to more directly look at the relation between retail trades around 13F disclosure periods and future stock returns. While the sophisticated screening hypothesized above suggests so, their success at inferring value-relevant information from trading disclosures also depends on their ability to evaluate their own private information, if they possess any, and that of sophisticated traders revealed in trading disclosures. The theory of informational cascades predicts that an uninformed individual, or one whose information has lower precision, blindly mimics the sophisticated trades. Bikhchandani et al. (1992), when discussing the case of information transmission in which individuals have different signal precisions, analytically show that a low-precision individual imitates a higher-precision predecessor. In practice, the uninformed individual likely follows a random subset of these trades by sophisticated investors or uses naïve heuristics, such as past performance and visibility to select the traders she tracks. As for the informed individual who wishes to combine her private information with that of sophisticated investors, she likely applies her own research and screening to the disclosed trades to discern the most profitable ones. In that vein, Cheynel and Levine (2015) argue that public disclosures allow partially informed traders to improve the precision of their private information, enhancing their information mosaic. This idea, known as the mosaic theory of financial analysis, is typically used to explain the behavior of financial analysts, who brings together bits of publicly available information with nonmaterial nonpublic information to arrive at a recommendation or forecast decision. An individual investor's analysis of a firm's valuation should follow a similar pattern. That said, it is not clear whether individuals possess the skills and resources to identify the most profitable trades from the trading disclosures. While individuals have some news interpreting skills (Akbas and Subasi, 2019), they ignore value-relevant information at other times (e.g., Lee, 1992; Maines and Hand, 1996; Blankespoor et al., 2019). Relying more on the recent research that characterizes at least a subset of individual investors as informed traders (e.g., Kaniel et al., 2012; Kelley and Tetlock, 2013; Boehmer et al., 2019), I conjecture that they have some skill in sorting through trading disclosures and using them to get more informed. If this is the case, the return predictability of individual investor trades around 13F disclosure periods should be higher around 13F disclosure periods than other times. I state the second sub-hypothesis of H2 accordingly:

H2b: The positive association between retail trades and future stock returns is stronger in 13F disclosure periods than other times.

Finally, as hypothesized in *H2a*, if individual investors mimic institutional trades that have predictive ability of upcoming earnings news (i.e. trades of transient and growth-oriented institutions), retail trades around 13F disclosure periods may impound some of the information to be revealed in the earnings announcement. While this effect also depends on the price impact of retail trades, there is evidence that retail trades move prices (Barber, Odean, and Zhu, 2009). This leads to my third hypothesis:

H3: Individual investor mimicking expedites price discovery of earnings news.

Chapter 3: Sample Selection, Research Design, and Descriptive Statistics

3.1 Sample

My sample includes 13F filings by institutional investors, from January 2007 to December 2017.[12] I obtain 13F filings from Thomson Reuters for the January 2007 – June 2013 period and from WRDS SEC Analytics Suite for the later period.[13] All institutions managing $100 million or more in Section 13F securities (long U.S. equity positions and some derivatives) are required to file quarterly 13F portfolio holdings reports within 45 days after each calendar quarter-end. I exclude institutions that hold more than 500 stock positions to eliminate firms with index funds. Insider trading data comes from Thomson Reuters insider filings database. I focus on first buys (purchases) of institutional investors as they are more likely to be informative.[14] I only use common stocks with share codes 10 and 11. As Thomson Reuters does not provide the exact filing date of 13F filings, I extract this information from the quarterly index files from SEC's EDGAR database.[15]

I obtain retail (individual investor) trades from TAQ database, using the method described in Boehmer et al. (2019). The method relies on the fact that in the U.S. retail order flow, but not institutional order flow, receives price improvement, and the majority of price-improved trades take place off-exchange and are reported to a Trade Reporting Facility (TRF). Retail-initiated buys

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[12] I start my analyses from 2007 as TAQ coverage in WRDS before 2007 is not intact.

[13] From June 2013 onwards, Thomson Reuters 13F data contains significant data errors. WRDS cleans and corrects the 13F data errors following the methodology described by Ben-David, Franzoni, Moussawi and Sedunov (2016) using parsed information directly from SEC 13F filings.

[14] In a long portfolio, purchases are more likely to be informative than sales as the choice of a stock to sell out of limited alternatives conveys less information (Chan and Lakonishok, 1993). However, in additional analyses, I examine institutional last sells as well.

[15] Quarterly index files can be accessed at https://www.sec.gov/Archives/edgar/full-index/.

(sells) are then identified as the transactions with prices slightly below (above) the round penny. For instance, when the bid (ask) price is \$12.01 (\$12.03), a retail buy order may execute at the price \$12.0299, i.e. with a 0.01 cent price improvement. A market maker provides the price improvement because (i) it gets to trade before other orders (ii) if it manages to keep the order flow balanced, earns a vast majority of the spread. To be conservative, trades at or near a half penny are not assigned to the retail category as they may be coming from institutions. Still, the approach allows the researchers to use the largest swath of retail trades of all available datasets. Further details of the approach are explained in Boehmer et al. (2019). This recent method has been used by Blankespoor et al. (2018, 2019) and Farrell et al., (2018).

3.2 Research Design

I first compute daily retail order imbalance as the difference in shares between retail bought and retail sold, scaled by the outstanding number of shares. As 13F filings are quarterly reports, I conduct my analyses on institutional trades at the quarterly level (Phillips et al., 2014; Lesmond and Stein, 2018).[16] I run the following OLS models:

$$\begin{aligned} OIB\ 2w_{it} = \quad & \beta_1 x Inst\ Buys\ 2w_{it} + \beta_2 x Lagged\ Mret_{it} + \beta_3 x Log\ MV_{it-1} \\ & + \beta_4 x Return\ Volatility_{it} + Firm\ FE + Year\text{-}Quarter\ FE + \varepsilon_{it}, \end{aligned} \tag{1}$$

$$\begin{aligned} OIB\ 1w_{it} = \quad & \beta_1 x Inst\ Buys\ 1w_{it} + \beta_2 x Lagged\ Mret_{it} + \beta_3 x Log\ MV_{it-1} \\ & + \beta_4 x Return\ Volatility_{it} + Firm\ FE + Year\text{-}Quarter\ FE + \varepsilon_{it}, \end{aligned} \tag{2}$$

$$\begin{aligned} OIB\ 3d_{it} = \quad & \beta_1 x Inst\ Buys\ 3d_{it} + \beta_2 x Lagged\ Mret_{it} + \beta_3 x Log\ MV_{it-1} \\ & + \beta_4 x Return\ Volatility_{it} + Firm\ FE + Year\text{-}Quarter\ FE + \varepsilon_{it}, \end{aligned} \tag{3}$$

[16] I exclude stock-quarters (about 21.6% of the initial sample) with an additional major information event within the period from two trading days before and one trading day after the deadline day (calendar day 45 of the quarter) to control for the possibility that retail trading surrounding 13F disclosure is driven by a concurrent information event. The 4-day period is when 13F disclosure is at its highest and a significant portion of 13F-related retail trading is likely to occur. Results are qualitatively the same if I keep these observations. I define major information events as earnings announcements, management forecasts and Form 8-K filings (Bushee, Jung, and Miller, 2011).

where i refers to the stock, and $OIB\ 2w_{it}$ is the retail order imbalance aggregated through the 2-week period around the 13F deadline day (i.e. days 39-52 of the quarter, day 45 being the deadline day) at quarter t, i.e. the quarter in which 13F filing is reported, computed by aggregating daily retail order imbalances. In the second and third models, I use $OIB\ 1w_{it}$, retail order imbalance aggregated at the seventh calendar week of the quarter t, (i.e. days 43-49 of the quarter) and $OIB\ 3d_{it,}$ retail order imbalance aggregated at the three trading days around the deadline day. $Inst\ Buys\ 2w_{it}$, $Inst\ Buys\ 1w_{it}$, and $Inst\ Buys\ 3d_{it}$ are the corresponding institutional buys, computed as the number of shares of the stock institutions bought as initial purchases (first buys), scaled by the outstanding number of shares, aggregated through the same period as the order imbalance variables. Note that, while institutional positions are disclosed in the concurrent quarter, institutional trades are made in the previous quarter. I add raw stock returns over the previous month of the first trading period (i.e. days 9-38 of the quarter) to control for information arrival (Phillips et al., 2014) and momentum effects (Akbas et al., 2019). I also control for the size of firms using the log of their market capitalization (*Log MV*), computed at the previous quarter-end to account for individual investors' tendency to prefer small stocks (Barber and Odean, 2000). Finally, I add return volatility of the stock for the past 30 days to account for possible individual investor attention to stocks with substantial recent fluctuations in price. I include firm- and quarter-fixed effects to account for potential cross-firm and cross-quarter heterogeneity in the panel.

The widest period of two weeks around the deadline day picks up a vast majority of the 13F disclosures that are made throughout the quarter while the narrowest period of three days still includes more than 35% of the 13F disclosures. A significant portion of the 13F-based retail trading is likely to occur in these periods. Figure 1 plots the average number of 13F institutions disclosing and the average dollar volume of their first buys per each day of the calendar quarter. Figure 2 illustrates the timeline of the chosen disclosure windows of two weeks, one week, and three days while Figure 3 shows the concentration of first buys in 13F filings for these windows.

3.3 Descriptive Statistics

I present descriptive statistics in Table 1. Retail order imbalance (OIB) variables have means and medians around 0%, consistent with individual investors not being a net buyer or seller in my sample, consistent with Boehmer et al. (2019). As expected, transient (dedicated) institutions trade more (less) than quasi-indexers, which fall in the middle. Hedge funds, particularly transient ones, also seem to be active. In terms of investment style, small growth and small value institutions trade substantially more, likely because they are able to accumulate a bigger percentage position with a comparable dollar amount investment. Pearson correlations in Panel B show that institutional buys are positively correlated with retail order imbalances, providing suggestive univariate evidence of mimicking. Lagged returns are negatively correlated with retail imbalance, consistent with individual investors being return contrarian in the short term (e.g., Grinblatt and Keloharju, 2000; Kaniel et al. 2008) while return volatility is positively correlated, consistent with individuals' preference for attention-grabbing stocks with high recent volatility in price. Individual investors in my sample do not seem to have a preference regarding firm size – market value is not significantly correlated with retail imbalance.

Chapter 4: Empirical Results

4.1 Individual Investors' Mimicking of 13F Institutions

Table 2 reports the estimation results of Equations (1)-(3). Column (1) shows that *Inst Buys*, i.e. institutional first buys over the two weeks centered around the 13F deadline day, is positively and significantly associated with retail trade imbalance, computed over the same period. In column (2), I include lagged market returns, log of market value of the firm and return volatility. The former is negative and significant throughout, consistent with individual investors being return contrarian in the short term (e.g., Grinblatt and Keloharju, 2000; Kaniel et al. 2008). Log of market capitalization (*Log MV*) is not significant, consistent with earlier univariate results. Return Volatility is positive and highly significant, consistent with expectations. Inferences are similar when I use smaller windows around 13F deadline day, one week in columns (3)-(4) and three days in columns (5)-(6). My use of smaller windows alleviates the concern that other events occurring in the longer periods might partially drive the results. My main finding is also economically significant. For instance, using the weekly results, an increase from the first quartile to the third quartile in purchases by institutional investors is associated with 52% increase in retail order imbalance, relative to the sample mean. Overall, findings are consistent with *H1*, which predicts that individual investors mimic institutional trades.

4.2 Types of 13F Institutions and Stocks Individual Investors Mimic

I next employ cross-sectional analyses to examine the types of 13F institutions individual investors seem to mimic. I employ the same specification in Table 2, but focusing on the week around the 13F deadline day. Panel A of Table 3 reports the results for limiting *Inst Buys* for certain types of institutions. When I use Bushee (2001)'s classification, consistent with my expectations, transient institutions seem to be mimicked more by individuals while there is no result for dedicated and quasi-indexer institutions.[17] Transient institutions seem to be the target of individuals who seek to benefit from 13F disclosures, likely because their investment horizons more closely match individuals (Barber and Odean, 2000; Bushee, 2001) and they are known to be more informed over short horizons (Ke and Petroni, 2004; Ke and Ramalingegowda, 2005; Yan and Zhang, 2007). Consistent with individuals' preference for transient institutions, Columns (4)-(5) show that individuals only mimic transient hedge funds, but not others.[18] In terms of the institutional investing style, individuals appear to screen for growth-style funds, which are known to hold stocks with high expected and future growth and more uncertain outcomes (Abarbanell, Bushee, and Smith Ready, 2003; Yan and Zhang, 2007). Overall, my findings corroborate *H2a*.

I also employ cross-sectional analyses based on firm characteristics, using variables measuring different types of firm risk. Using beta, stock return volatility and idiosyncratic risk, I show in Panel B of Table 3 that individual investors screen for riskier stocks when they mimic institutional trades, consistent with earlier evidence and their inherent preference for these type of stocks (Kumar, 2009; Mitton and Vorkink, 2007). Overall, my findings presented in Table 3 support H2a and provides initial evidence of H2, suggesting that individual investors likely benefit from their screening of institutional trades.

[17] I thank Brian Bushee for sharing his institutional investor classification data, which is available until 2017.
[18] I thank Vikas Agarwal for sharing his hedge fund data, which is available until 2015. The data was constructed for the following studies: Agarwal, Jiang, Tang, Yang (2013), Agarwal, Fos, Jiang (2013) and Agarwal, Ruenzi, and Weigert (2017).

4.3 Profitability of Individual Trading on 13F Disclosure Periods

My analysis thus far shows that individual investors follow trades of institutional investors around 13F disclosure periods. In this section, I examine whether the predictive ability of retail trades, which prior literature shows to be strongly positive, is higher in these periods than other periods of the quarter. If individual investors are able to apply sophisticated screening to the revealed institutional trades, in effect processing the new information effectively, they might benefit from these trading disclosures, resulting in a higher predictive coefficient.

To examine this question, I estimate weekly Fama-Macbeth (1973) regressions of the following form:

$$\begin{aligned} Return_{it+1,t+20} = {} & \beta_1 xOIBw_{it} + \beta_2 x13F\ Week_{it} + \beta_3 xOIBw_{it} x13F\ Week_{it} \\ & + \beta_4 xLagged\ Mret_{it} + \beta_5 xLog\ MV_{it} + \beta_6 xBTM_{it} + \\ & \beta_7 xReturn\ Volatility_{it} + \varepsilon_{it}, \end{aligned} \tag{4}$$

where $Return_{it+1,t+20}$ is compounded buy and hold abnormal and raw returns over trading days t+1 through t+20. Abnormal returns are computed as raw return minus CRSP value-weighted index return. $OIBw_{it}$ is the decile ranked weekly retail order imbalance of each week of the quarter, computed by aggregating daily retail order imbalances ((buy-sell)/shares outstanding). I define the disclosure period as the 7th week of the calendar quarter (*13F Week*), which includes the 13F deadline day. I also control for well-known factors explaining future returns. I control for momentum effect using $Lagged\ Mret_{it}$, defined as the raw stock returns over the previous month ending one week before the deadline day (i.e. days 9-38 of the quarter). I control for the size effect using $Log\ MV_{it}$, defined as the log of firm's market capitalization, computed at the previous quarter-end. I include *BTM*, the book-to-market ratio, computed at the previous quarter-end to control for the book-to-market factor. I also include *Return Volatility* to be consistent with prior specifications. I correct for possible serial correlation in the regression via the Newey-West (1987) procedure with 4 weekly lags.

In Panel A of Table 4, I present the analysis for buy and hold returns for the next 20 trading days after the week ends. Consistent with the findings of recent literature (e.g., Kaniel Liu, Saar, and Titman, 2012; Boehmer et al., 2019; Akbas and Subasi, 2019), I find a strong positive relation between net trading by individual investors and subsequent stock returns across the board – *OIBw* is positive and significant. More importantly, the positive and highly significant loading on *OIBw * 13F Week* shows that the predictive ability of individual investors' trades increases significantly on the week around the 13F disclosure deadline.[19] The effect is also economically significant: The relation between net trading by individual investors and future returns is 6.3% larger on the 13F disclosure week when compared to the other weeks of the quarter.[20] This finding, supporting H2b, is consistent with individual investors benefiting from their processing of institutional trades, lending further support to H2.

An alternative explanation to my main findings is that individual investors may be buying the stocks in the 13F disclosure periods simply because revelation of institutional purchases through 13F filings increases the visibility of those stocks, not because they actively try to analyze and integrate those trades into their trading decisions. Consistent with this explanation, Barber and Odean (2008) find that individual investors tend to buy attention-grabbing stocks. If that is indeed the case, price pressure from excess demand to those stocks may explain the positive association between net retail trading volume and future returns, rather than individual investors being skilled interpreters of the disclosed trades. This reasoning implies that over longer horizons, the stock

[19] My results are robust to using the characteristics-adjusted returns of Daniel et al. (1997) (DGTW return).
[20] From Column (3), the coefficient on the interaction divided by the coefficient on OIB1w, i.e. 0.050/0.791.

price should revert back to fundamentals, eroding the return predictability of retail trades. I test this alternative explanation by introducing longer period return tests. Panel B of Table 4 shows the results of the analyses. For both raw and abnormal future returns over 90-day holding periods, the predictability of retail trades is still higher during the 13F disclosure week, suggesting that this alternative explanation is unlikely to explain my results.

4.4 Price Discovery Effects

Next, I examine the impact of the individual investor mimicry on the market. First, I examine whether retail trading in the 13F disclosure week accelerates the price discovery of upcoming earnings news. As trades of short-term institutions predict future earnings surprises (Ke and Petroni, 2004; Yan and Zhang, 2007), I expect heavy individual mimetic trading to impound some of the information to be revealed in the earnings. I run the following OLS model of the ERC framework:

$$\begin{aligned} CAR[-1,+1]_{it} = {} & \beta_1 x SUE_{it} + \beta_2 x OIB1w_{it} + \beta_3 x SUE_{it} x OIB1w_{it} \\ & + Controls + Firm\ FE\ + Year - Quarter\ FE\ + \varepsilon_{it}, \end{aligned} \tag{5}$$

where *CAR[-1,+1]* is the Cumulative abnormal returns, defined as the raw returns adjusted for the value-weighted market return over the three days around the earnings announcement date. *SUE* is Standardized unexpected earnings, defined as the actual earnings minus the most recent median analyst consensus forecast, scaled by the end of quarter stock price. $OIB\ 1w_{it}$ is the decile ranked weekly retail order imbalance of in the week around 13F deadline, computed by aggregating daily retail order imbalances ((buy-sell)/shares outstanding). Control variables include Share Turnover, Log # Analysts, Std SUE, Log Firm Age, Q4 Indicator, EA Day of Quarter and CAR[-2,-62], all of which are borrowed from prior research (Madsen, 2017; Zhang, Cai, and Keasey, 2013). Control variables are defined in the Appendix. Table 5 presents the estimation results. Columns (2) and (4) include interactions of *SUE* with the control variables whereas Columns (3) and (4) have institutional buys as a control to better isolate the effect of the retail trades. Across the board, I find that the earnings response coefficient (ERC) is lower when retail order imbalance around the 13F deadline week is higher – interaction variable is negative and significant. The effect is also economically meaningful: When net trading by individual investors increases from the 3rd decile to the 7th, the ERC declines by 13%, an economically significant result.[21] This finding provides evidence for H3. Next, I directly look at the price adjustment after 13F filings themselves. Panel B of Table 5 presents the results. Defined as the fraction of future 60-day returns realized in the 5-day period around the 13F deadline day, price adjustment is 8.1% (11.2%) when retail order imbalance in the 5-day period is in the lowest (highest) tercile. The difference, 3.1%, represents a 38.3% improvement. Overall, my findings from this section suggests that individual investor mimicking from trading disclosures seems to aid market efficiency.

4.5 Alternative Explanation: Earnings Channel

In this section, I explore an alternative explanation to my findings. As I discuss earlier, transient institutions' trading predicts earnings surprises (Yan and Zhang, 2007). If individual investors are merely responding to the earnings announcements made earlier in the quarter with a delay, without regard to the trading disclosures, their trades may still be correlated with institutional first buys. I address this explanation in two ways. First, I restrict my sample to stock-quarters in which earnings are reported *after* the 13F deadline window, and control for the previous quarter's earnings news in Columns (1) and (2) of Table 6. Second, when examining the stock-quarters in which earnings are reported *before* the 13F deadline window, I control for both current

[21] From Column (4), 0.4*(-0.810)/2.488.

and previous quarters' earnings news in Columns (3) and (4). The coefficient on *Inst Buys* remain positive and significant, suggesting that my inferences are robust to considering this alternative explanation.

4.6 Falsification Tests

While my earlier results, especially from short windows of one week and three days provides strong evidence of mimicking, a concern that remains is that an extraneous factor may drive a concurrent and lead-lag relation between individual and institutional trades, in which case trades of the two groups might be spuriously correlated. I conduct some falsification tests to address this concern, using unintuitive accumulation periods for retail trades and institutional holdings disclosures that cannot be explained by mimicking.

Results of these analyses presented in Table 7 reveal that the timing of first buys and retail trading needs to be in sync for the results to hold, i.e. my results are not driven by lead-lag relationships possibly caused by an extraneous variable. Column (2) and (4) show that there is no relation between 13F deadline period first buys and retail trading *before* that period, i.e. earlier in the quarter. Column (6) similarly shows that there is no significant association between institutional buys revealed in the *next* quarter's deadline week and retail trading in the current quarter's deadline week.

4.7 Last Sells

First buys of institutions, while considered the most informative (Baker et al., 2010, Rhinesmith, 2015) are not the only possible source of information within 13F portfolio holdings disclosures. Specifically, institutional last sells typically represent some conviction that they are bearish about the stock, other explanations being the price reaching their target, liquidity needs, portfolio rebalancing etc. To explore whether individuals mimic institutional last sells, I rerun my main tests focusing on this group of trades. Results presented in Table 8 are largely consistent with this view—*Inst Sells* is significantly related to retail order imbalances (*OIB*) for one week and three days analyses, but not for the two weeks analysis.

4.8 Individual Investor Mimicking from Insider Trades

Next, I expand the definition of "trading disclosures" to include another group of sophisticated investors, corporate insiders. I gather all insider trades for my sample period, 2007-2017 from Thomson Reuters insider filings database.[22] I focus on insider purchases as they are more likely to be informative (Wang, Shin, and Francis, 2012). As Form 4s are not periodic, unlike 13Fs, the natural level to study them is at the filing-day level. I only aggregate filings if they are reported by an insider on the same day for the same stock. Taking the SEC filing date as the event date, I examine individual investor trades on the event day and the following day.[23] I run the following OLS model on my insider trades sample:

$$\begin{aligned} OIB\ 2d_{it} = \quad & \beta_1 xInst\ Sells\ 3d_{it} + \beta_2 xLagged\ Mret_{it} + \beta_3 xLog\ MV_{it-1} \\ & + \beta_4 xReturn\ Volatility_{it} + Firm\ FE + Year\text{-}Quarter\ FE + \varepsilon_{it}, \end{aligned} \tag{6}$$

where *OIB* $2d_{it}$ is the retail order imbalance for the event window, i.e. two days, computed by aggregating daily retail order imbalances of the event day and the following day. *Insider* $Buys_{it}$ is computed as the number of shares purchased by the insider, scaled by the outstanding number of shares. Table 9 presents the results of my analyses on whether individuals mimic insider purchases.

[22] Insiders must file Form 4 reports within two business days following their stock transactions in SEC Form 4. While they cannot trade their firms' stock on material nonpublic information, they are free to trade based on their insights and assessments.
[23] Similar to my treatment of other major information events for the institutional sample, I exclude observations (about 23.8% of the initial sample) if there is a major information event in the Form 4 filing date as well as the previous and the following days. Results are qualitatively the same if I keep these observations.

In column (1), I find a positive and significant association between insider purchases and retail order imbalance in the 2-day window including the filing date, consistent with mimicking.

To examine the sophistication of individuals' mimicry of insiders, I follow Cohen, Malloy and Pomorski (2012) and classify insider trades into "routine" vs "opportunistic" trades, based on the timing and frequency of their purchases. Specifically, if an insider makes at least one trade, either a purchase or a sale, in each of the three preceding years, it is assigned from that year onwards as either "routine" or "opportunistic". If the insider places a trade for all three years in the same calendar month, it is assigned to the "routine" category. All the remaining insiders are defined

"opportunistic". Cohen et al. (2012) show that routine trades are not informative about future returns, while opportunistic trades, particularly by local insiders are very informative. Consistent with sophisticated screening, I find that individuals do not mimic routine trades (columns 3 and 4), but do mimic trades of opportunistic local insiders (column 2). Columns (5)-(8) present the cross-sectional analyses by insider role. Interestingly, individual investors do not follow the trades of top executives (top 5 executives defined as CEO, CFO, COO, President, and Chairman of board, following Beneish and Vargus, 2002) who may be motivated by more than just profit, e.g., showing their trust in the firm. Individual investors seem to mimic insiders who are not top executives of the firm, especially non-executive directors.

4.9 Robustness Tests

I conduct several robustness tests to strengthen my inferences. My results are robust to (i) using an alternative measure of institutional first buys based on the number of institutions buying, instead of the original volume-based measure, (ii) expanding the 13F disclosure window to the whole quarter, (iii) excluding the financial crisis period, (iv) excluding stock-quarters in which there are no institutional first buys, and (v) including observations with a major information event (earnings announcements, management forecasts and Form 8-K filings) in different periods around deadline day. I do not tabulate the results of these robustness tests for brevity.

Chapter 5: Conclusion

In this study, I explore trading disclosures by 13F institutions as an information source for individual investors. Building on prior research that characterizes these market participants as sophisticated investors, I argue that individuals, particularly if they are able to employ sophisticated screening techniques or combine their private information with that revealed in these disclosures, might gain a comparative edge. I find evidence of their mimicking from institutional investors, particularly transient and growth-style institutions who share similarly short investment horizons and known to be more informed in the short-term. Individual investors also seem to benefit from their selective mimicking of institutional trading disclosures as the positive relationship between retail order imbalance and future stock returns is more pronounced in the 13F deadline week than other weeks of the calendar quarter. Mimicking trading has positive effects on the market – it accelerates the price discovery of upcoming earnings news and the information revealed in 13F disclosures. SEC-mandated trading disclosures seem to help level the informational playing field, a longtime goal of the Commission.

Appendix

Variable Definitions

The sample period runs from January 2007 to December 2017. I winsorize all continuous variables at the 1 percent level and standardize all variables to have mean zero and variance one.

Variable	Definition
OIB 2w	Retail order imbalance ((buy-sell)/shares outstanding) over the two weeks around the 13F deadline day (day 45 of the calendar quarter), i.e. over days 39 to 52 of the calendar quarter.
OIB 1w	Retail order imbalance over the week around the 13F deadline day.
OIB 3d	Retail order imbalance over the three trading days centered on the deadline day.
Inst Buys	The number of shares institutions bought as initial purchases (first buys), scaled by the outstanding number of shares, aggregated in different periods, similarly to OIB variables.
Lagged Mret	Raw stock returns over the previous month.
Log MV	Natural log of firm's market capitalization, computed at the previous quarter-end.
Return volatility	Standard deviation of the raw stock returns over the previous month.
Beta	A measure of market risk, estimated by regressing daily individual stock returns over the previous calendar year on the contemporaneous CRSP value-weighted market returns.
Idiosyncratic risk	Annualized standard deviation of the residuals from regressing daily individual stock returns over the same period on the contemporaneous CRSP value-weighted market returns.
BTM	Book-to-market ratio, computed at the previous quarter-end.
CAR[-1,+1]	Cumulative abnormal returns, defined as the raw returns adjusted for the value-weighted market return over the three days around the earnings announcement date.
SUE	Standardized unexpected earnings, defined as the actual earnings minus the most recent median analyst consensus forecast, scaled by the end of quarter stock price.
Share Turnover	The average monthly share turnover (volume/shares outstanding) measured over the previous year.
Log # Analysts	Natural log of one plus the number of analysts covering the firm.
Std SUE	Standard deviation of the SUE over the two-year period prior to the earnings announcement.
Log Firm Age	Natural log of the years firm has been in CRSP.
Q4 Indicator	1 if the current quarter is the last calendar quarter of the year.

EA Day of Quarter	Number of days from the beginning of the calendar quarter until earnings announcement.
CAR[-2,-62]	Cumulative abnormal returns over the sixty days ending two days before the earnings announcement date.
Price Adjustment	Fraction of future 60-day returns realized in the 5-day period around the 13F deadline day.
OIB2d	Retail order imbalance over the two days around the Form 4 filing, i.e. filing date and the following day.
Insider Buys	Number of shares purchased by the insider, scaled by the outstanding number of shares.

Table 1: Descriptive statistics

Panel A: Summary statistics

	N	Mean	Std. Dev	P1	P5	P25	P50	P75	P95	P99
OIB 2w	109,213	0%	0.108%	-0.389%	-0.156%	-0.036%	-0.002%	0.029%	0.165%	0.471%
OIB 1w	109,213	0%	0.066%	-0.238%	-0.095%	-0.021%	-0.001%	0.018%	0.102%	0.288%
OIB 3d	109,213	0%	0.049%	-0.181%	-0.071%	-0.015%	0%	0.013%	0.074%	0.212%
Inst Buys 2w	109,213	1.949%	3.539%	0%	0%	0.135%	0.801%	2.333%	7.474%	16.070%
Inst Buys 1w	109,213	1.230%	2.183%	0%	0%	0.006%	0.346%	1.409%	5.556%	12.812%
Inst Buys 3d	109,213	1.157%	2.096%	0%	0%	0%	0.303%	1.295%	5.319%	12.281%
Lagged Mret	109,213	0.65%	13.99%	-37.00%	-21.67%	-6.82%	0.22%	7.25%	24.64%	50.00%
MV (in $ millions)	109,213	4,885	21,345	10	29	142	497	2,163	19,439	84,572
Return Volatility	109,213	0.028	0.019	0.005	0.009	0.016	0.023	0.035	0.067	0.109
Transient Inst Buys 1w	109,213	0.665%	1.323%	0%	0%	0%	0.106%	0.676%	3.350%	7.784%
Dedicated Inst Buys 1w	109,213	0.031%	0.205%	0%	0%	0%	0%	0%	0.003%	1.755%
Quasi-Indexer Inst Buys 1w	109,213	0.296%	0.784%	0%	0%	0%	0.001%	0.148%	1.764%	4.934%
Transient Hedge Fund Buys 1w	92,338	0.424%	0.970%	0%	0%	0%	0.024%	0.341%	2.330%	5.683%
Other Hedge Fund Buys 1w	92,338	0.202%	0.689%	0%	0%	0%	0%	0.024%	1.209%	4.545%
Large Growth Inst Buys 1w	109,213	0.051%	0.211%	0%	0%	0%	0%	0.000%	0.251%	1.577%
Small Growth Inst Buys 1w	109,213	0.525%	1.220%	0%	0%	0%	0.007%	0.404%	2.981%	7.305%
Large Value Inst Buys 1w	109,213	0.041%	0.160%	0%	0%	0%	0%	0.003%	0.199%	1.207%
Small Value Inst Buys 1w	109,213	0.381%	0.860%	0%	0%	0%	0.043%	0.318%	1.996%	5.373%
Return Tests										
Abnormal return [1,20]	1,149,862	0.12%	11.72%	-32.71%	-18.45%	-5.78%	-0.34%	5.27%	20.14%	43.21%
Raw return [1,20]	1,149,862	0.90%	12.89%	-35.46%	-20.00%	-5.62%	0.59%	6.80%	22.64%	46.77%
Abnormal return [1,60]	1,149,862	0.89%	24.93%	-56.88%	-36.99%	-12.84%	-0.96%	11.60%	45.20%	97.37%
Raw return [1,60]	1,149,862	4.33%	27.91%	-61.14%	-39.13%	-11.15%	2.69%	16.92%	53.07%	110.00%
Lagged Mret	1,149,862	1.01%	13.02%	-35.31%	-19.95%	-5.56%	0.65%	6.84%	22.92%	48.63%
MV (in $ millions)	1,149,862	3,835	11,197	9	25	122	454	2,083	18,958	81,747
BTM	1,149,862	0.70	0.60	-0.01	0.10	0.31	0.55	0.88	1.78	3.72
Return Volatility	1,149,862	0.028	0.019	0.006	0.009	0.015	0.023	0.035	0.066	0.109

Table 1 Cont'd.

	N	Mean	Std. Dev	P1	P5	P25	P50	P75	P95	P99
<u>*Price Discovery Tests*</u>										
CAR[-1,+1]	8,348	0.00%	10.76%	-27.16%	-15.96%	-4.85%	-0.19%	4.68%	15.71%	29.81%
SUE	8,348	-0.009	0.151	-1.033	-0.072	-0.004	0.000	0.004	0.040	0.751
BTM	8,348	0.58	0.55	-0.97	0.00	0.25	0.48	0.78	1.60	2.95
Share Turnover	8,348	0.18	0.16	0.02	0.03	0.08	0.14	0.23	0.50	0.92
Log # Analysts	8,348	6.20	5.39	1	1	2	5	8	17	26
Beta	8,348	1.16	0.54	0.02	0.29	0.78	1.12	1.50	2.11	2.61
Std SUE	8,348	0.108	0.557	0.000	0.001	0.002	0.006	0.018	0.258	4.819
Firm Age	8,348	2.35	0.95	0.69	0.69	1.61	2.48	3.04	3.76	4.19
Q4 Indicator	8,348	0	0	0	0	0	0	0	0	1
EA Day of Quarter	8,348	62	10	50	51	55	60	69	82	90
CAR[-2,-62]	8,348	1.44%	21.98%	-51.03%	-30.11%	-10.28%	-0.73%	9.94%	40.99%	91.98%
<u>*Insider Trading Sample*</u>										
OIB 2d	552,704	0.000%	0.038%	-0.141%	-0.054%	-0.011%	-0.001%	0.010%	0.058%	0.171%
Insider Buys	552,704	0.036%	0.097%	0%	0%	0.001%	0.006%	0.024%	0.159%	0.718%
Lagged Mret	552,704	1.33%	12.49%	-36.42%	-19.85%	-4.81%	1.40%	7.32%	21.66%	43.52%
MV (in $ millions)	552,704	9,559	25,926	21	57	350	1,391	5,605	46,296	177,973
Return Volatility	552,704	0.025	0.017	0.006	0.008	0.014	0.020	0.031	0.060	0.099
Opportunistic Local Buys	87,648	0.037%	0.090%	0%	0%	0.002%	0.009%	0.031%	0.166%	0.551%
Routine Local Buys	126,401	0.021%	0.066%	0%	0%	0%	0.003%	0.014%	0.091%	0.325%
Routine Buys	181,739	0.020%	0.065%	0%	0%	0%	0.003%	0.013%	0.088%	0.316%
Top-5 Exec Buys	118,241	0.064%	0.124%	0%	0%	0.005%	0.019%	0.060%	0.296%	0.718%
Non-Top-5 Exec Buys	434,463	0.028%	0.087%	0%	0%	0.001%	0.004%	0.018%	0.113%	0.606%
Non-Exec Director Buys	209,829	0.019%	0.062%	0%	0%	0.001%	0.003%	0.013%	0.076%	0.294%
Other Non-Top-5 Buys	224,634	0.036%	0.104%	0%	0%	0.001%	0.006%	0.023%	0.156%	0.718%

Table 1 Cont'd.

Panel B: Pearson (below the diagonal) and Spearman (above the diagonal) correlations for the main sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
(1) OIB 2w		0.69*	0.54*	-0.01	-0.01	-0.01*	-0.03*	0.00	0.02*	-0.01	0.01	-0.01	0.00	0.00	0.00	0.00	0.00	-0.01*
(2) OIB 1w	0.73*		0.74*	0.00	0.00	-0.01	-0.03*	0.00	0.01*	0.00	0.00	-0.01*	-0.01	0.00	0.00	0.00	0.00	-0.01*
(3) OIB 3d	0.59*	0.79*		0.00	0.00	0.00	-0.02*	0.00	0.01*	0.00	0.00	-0.01*	0.00	0.00	0.00	0.00	0.00	-0.01*
(4) Inst Buys 2w	0.01*	0.01*	0.01*		0.88*	0.86*	0.02*	0.38*	-0.03*	0.71*	0.08*	0.51*	0.61*	0.38*	0.22*	0.63*	0.23*	0.61*
(5) Inst Buys 1w	0.01*	0.02*	0.01*	0.85*		0.95*	0.02*	0.40*	-0.02*	0.79*	0.09*	0.57*	0.67*	0.42*	0.25*	0.69*	0.26*	0.69*
(6) Inst Buys 3d	0.01*	0.01*	0.01*	0.84*	0.98*		0.02*	0.41*	-0.04*	0.78*	0.09*	0.55*	0.67*	0.42*	0.24*	0.68*	0.26*	0.67*
(7) Lagged Mret	-0.04*	-0.03*	-0.03*	0.01	0.01	0.00		0.04*	-0.05*	0.03*	0.00	0.04*	0.03*	0.03*	0.04*	0.02*	0.04*	0.04*
(8) MV (in $ millions)	0.00	0.00	0.00	0.09*	0.11*	0.11*	0.00		-0.38*	0.46*	0.04*	0.41*	0.47*	0.27*	0.41*	0.41*	0.44*	0.41*
(9) Return Volatility	0.04*	0.03*	0.03*	-0.01	0.00	0.00	0.02*	-0.35*		-0.02*	0.00	-0.10*	-0.06*	-0.07*	-0.11*	0.00	-0.13*	-0.08*
(10) Transient Inst Buys 1w	0.01*	0.01*	0.01*	0.65*	0.77*	0.75*	0.01	0.14*	0.01*		0.06*	0.36*	0.80*	0.27*	0.25*	0.70*	0.27*	0.66*
(11) Dedicated Inst Buys 1w	0.00	0.00	0.00	0.28*	0.30*	0.31*	0.00	0.00	0.02*	0.10*		0.05*	0.06*	0.10*	0.05*	0.08*	0.04*	0.07*
(12) Quasi-Indexer Buys 1w	0.00	0.00	0.00	0.48*	0.57*	0.54*	0.01*	0.07*	-0.01*	0.23*	0.08*		0.35*	0.43*	0.33*	0.42*	0.35*	0.51*
(13) Tran. Hedge F. Buys 1w	0.01*	0.01*	0.01*	0.58*	0.68*	0.67*	0.00	0.15*	-0.01*	0.87*	0.11*	0.21*		0.27*	0.26*	0.63*	0.28*	0.58*
(14) Other Hedge F. Buys 1w	0.00	0.00	0.00	0.48*	0.55*	0.54*	0.01	-0.01	-0.01*	0.21*	0.40*	0.49*	0.21*		0.20*	0.34*	0.20*	0.32*
(15) Large Gr. Inst Buys 1w	0.00	0.01	0.01	0.20*	0.25*	0.24*	0.02*	0.18*	-0.02*	0.18*	0.06*	0.30*	0.15*	0.09*		0.23*	0.27*	0.20*
(16) Small Gr. Inst Buys 1w	0.01*	0.01*	0.01*	0.64*	0.75*	0.74*	0.00	0.08*	0.03*	0.78*	0.25*	0.39*	0.69*	0.39*	0.11*		0.23*	0.37*
(17) Large Va. Inst Buys 1w	0.00	0.00	0.00	0.20*	0.23*	0.22*	0.01*	0.16*	-0.03*	0.15*	0.03*	0.33*	0.14*	0.09*	0.09*	0.10*		0.23*
(18) Small Va. Inst Buys 1w	0.00	0.01	0.00	0.55*	0.64*	0.62*	0.01*	0.08*	-0.02*	0.56*	0.22*	0.51*	0.51*	0.37*	0.08*	0.28*	0.12*	

Table 2: Individual investors' mimicking of trades of 13F institutions

This table reports coefficient estimates from the following panel regression:

$$OIB_{it} = \beta_1 * Inst\ Buys_{it} + \beta_2 * Lagged\ Mret_{it} + \beta_3 * Log\ MV_{it} + \beta_4 * Return\ Volatility + Firm\ FE + Year\text{-}Quarter\ FE + \varepsilon_{it},$$

where OIB_{it} is the retail order imbalance in percentile at different periods around 13F deadline day (day 45 of the quarter), computed by aggregating daily retail order imbalances ((buy-sell)/shares outstanding). In columns 1-2 (3-4), aggregation period is two weeks (one week) around the deadline day. In columns 5 and 6, aggregation period is just the three trading days centered on the deadline day. Inst $Buys_{it}$ is the institutional first buys, computed as the number of shares of the stock institutions bought as initial purchases (first buys), scaled by the outstanding number of shares, disclosed in the same period as OIB_{it}. Lagged $Mret_{it}$ is the raw stock returns over the previous month of the first trading period (i.e. days 9-38 of the quarter). Log MV_{it} is the log of firm's market capitalization, computed at the previous quarter-end. Return Volatility is the standard deviation of the raw stock returns over the previous month. The sample period is January 2007-December 2017. All specifications include firm and year-quarter fixed effects and standard errors are clustered by firm. The *t*-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Period around mid-quarter:	*Two weeks*		*One week*		*Three days*	
	(1)	(2)	(3)	(4)	(5)	(6)
Inst Buys	0.738*	0.904**	1.041**	1.153***	1.001**	1.063***
	(1.78)	(2.17)	(2.50)	(2.76)	(2.43)	(2.58)
Lagged Mret		-5.192***		-3.010***		-2.951***
		(-10.83)		(-6.25)		(-6.24)
Log MV		-1.200		-0.752		0.341
		(-0.67)		(-0.44)		(0.20)
Return Volatility		4.903***		3.322***		2.264***
		(7.17)		(4.96)		(3.42)
Intercept	3.169*	6.708***	3.669*	5.928***	2.774	4.516**
	(1.69)	(3.54)	(1.78)	(2.84)	(1.31)	(2.11)
Observations	109,213	109,213	109,213	109,213	109,213	109,213
Adjusted R^2	0.031	0.034	0.027	0.028	0.023	0.024

Table 3: Cross-sectional analyses: Types of 13F institutions and stocks individual investors mimic

This table reports coefficient estimates from the following panel regression:

$$OIB\ 1w_{it} = \beta_1 * Inst\ Buys_{it} + \beta_2 * Lagged\ Mret_{it} + \beta_3 * Log\ MV_{it} + \beta_4 * Return\ Volatility + Firm\ FE + Year\text{-}Quarter\ FE + \varepsilon_{it},$$

where OIB $1w_{it}$ is the retail order imbalance at the one week around 13F deadline day (day 45 of the quarter), computed by aggregating daily retail order imbalances ((buy-sell)/shares outstanding). Inst $Buys_{it}$ is the institutional first buys, computed as the number of shares of the stock institutions bought as initial purchases (first buys), scaled by the outstanding number of shares, disclosed in the same period as OIB $1w_{it}$. Lagged $Mret_{it}$ is the raw stock returns over the previous month. Log MV_{it} is the log of firm's market capitalization, computed at the previous quarter-end. In Panel A, institutional buys are aggregated based on institutional investor type. In Panel B, sample is split based on proxies of stock risk. Beta is estimated by regressing daily individual stock returns over the previous calendar year on the contemporaneous CRSP value-weighted market returns. Return volatility is the standard deviation of the raw stock returns over the same period. Idiosyncratic risk is the annualized standard deviation of the residuals from regressing daily individual stock returns over the same period on the contemporaneous CRSP value-weighted market returns. The sample period is January 2007-December 2017. All specifications include firm and year-quarter fixed effects and standard errors are clustered by firm. The *t*-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: By Institutional Investor Type

	Transient Inst.	*Dedicated Inst.*	*Quasi-Indexer Inst.*	*Transient Hedge Funds*	*Other Hedge Funds*	*Large Growth Inst.*	*Small Growth Inst.*	*Large Value Inst.*	*Small Value Inst.*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Inst Buys	1.278***	0.178	-0.079	0.797*	0.029	0.721**	0.947**	0.274	0.518
	(2.79)	(0.46)	(-0.21)	(1.73)	(0.08)	(2.00)	(2.13)	(0.80)	(1.32)
Lagged Mret	-3.008***	-2.996***	-2.994***	-3.649***	-3.639***	-2.995***	-3.003***	-2.994***	-3.000***
	(-6.25)	(-6.22)	(-6.22)	(-7.20)	(-7.18)	(-6.22)	(-6.24)	(-6.22)	(-6.23)
Log MV	-0.899	-0.451	-0.452	1.005	1.223	-0.616	-0.753	-0.491	-0.518
	(-0.52)	(-0.26)	(-0.26)	(0.51)	(0.62)	(-0.36)	(-0.44)	(-0.28)	(-0.30)
Return Volatility	3.312***	3.286***	3.285***	3.793***	3.765***	3.280***	3.310***	3.288***	3.298***
	(4.95)	(4.92)	(4.91)	(5.28)	(5.25)	(4.91)	(4.95)	(4.92)	(4.93)
Intercept	6.155***	6.152***	6.146***	6.274***	6.255***	6.182***	6.137***	6.169***	6.129***
	(2.94)	(2.94)	(2.94)	(3.00)	(2.99)	(2.96)	(2.94)	(2.95)	(2.93)
Observations	109,213	109,213	109,213	92,338	92,338	109,213	109,213	109,213	109,213
Adjusted R^2	0.028	0.028	0.028	0.027	0.027	0.028	0.028	0.028	0.028

Table 3 Cont'd.

Panel B: By Stock Risk

	Beta			*Return Volatility*			*Idiosyncratic Risk*		
	Low	*Mid*	*High*	*Low*	*Mid*	*High*	*Low*	*Mid*	*High*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Inst Buys	0.300	0.684	2.002***	-0.285	-0.032	2.994***	0.209	0.632	1.769**
	(0.42)	(0.90)	(2.65)	(-0.46)	(-0.05)	(3.41)	(0.29)	(0.99)	(2.33)
Lagged Mret	-2.489***	-2.563***	-3.570***	-3.685***	-2.866***	-2.885***	-3.673***	-3.188***	-2.829***
	(-2.89)	(-2.78)	(-4.47)	(-3.17)	(-3.48)	(-4.23)	(-4.10)	(-4.16)	(-3.74)
Log MV	-11.182***	-1.331	5.492*	0.228	1.394	-0.612	3.672	0.830	0.753
	(-3.32)	(-0.35)	(1.78)	(0.07)	(0.48)	(-0.22)	(1.04)	(0.27)	(0.27)
Return Volatility	0.659	5.670	2.545	-2.580	7.657*	12.192**	-2.759	7.719**	6.149
	(0.20)	(1.55)	(0.56)	(-0.74)	(1.71)	(2.04)	(-0.77)	(2.07)	(1.22)
Intercept	0.003	0.053	0.018	0.000	0.037	0.067	-0.029	0.068*	0.056
	(0.10)	(1.46)	(0.40)	(0.00)	(0.99)	(1.34)	(-0.85)	(1.83)	(1.11)
Observations	36,415	36,406	36,386	36,408	36,404	36,401	36,421	36,399	36,387
Adjusted R^2	0.034	0.043	0.039	0.058	0.030	0.014	0.035	0.029	0.020

Table 4: 13F disclosure period and predictive ability of weekly retail trading order imbalance for future stock returns

This table reports coefficient estimates from weekly Fama-Macbeth (1973) regressions of the following form:

$$Return_{it+1,t+20} = \beta_1 * OIB\,1w_{it} + \beta_2 * 13F\ Week_{it} + \beta_3 * OIB1w_{it} * 13F\ Week_{it} + \beta_4 * Lagged\,Mret_{it} + \beta_5 * Log\,MV_{it} + \beta_6 * BTM_{it} + \beta_7 * Return\ Volatility_{it} + \varepsilon_{it},$$

where $Return_{it+1,t+20}$ is compounded returns over trading days t+1 through t+20. In Panel B, $Return_{it+1,t+90}$, compounded returns over trading days t+1 through t+90 is used. Abnormal returns are computed as raw return minus CRSP value-weighted index return. $OIB1w_{it}$ is the decile ranked weekly retail order imbalance of each week of the quarter, computed by aggregating daily retail order imbalances ((buy-sell)/shares outstanding). 13F Week is the 7th week of the calendar quarter, which includes the 13F deadline day. Lagged $Mret_{it}$ is the raw stock returns over the previous month of the first trading period (i.e. days 9-38 of the quarter). Log MV_{it} is the log of firm's market capitalization, computed at the previous quarter-end. BTM is the book-to-market ratio, computed at the previous quarter-end. Return Volatility is the standard deviation of the raw stock returns over the previous month. The sample period is January 2007-December 2017. The *t*-statistics use standard errors corrected for serial correlation via the Newey-West (1987) procedure with 4 weekly lags. The *t*-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Buy and hold returns for the next 20 trading days

	Abnormal return [1,20]			*Raw return [1,20]*		
	(1)	(2)	(3)	(4)	(5)	(6)
OIB 1w	0.977***	0.881***	0.791***	0.865***	0.792***	0.716***
	(6.50)	(7.11)	(6.48)	(6.54)	(7.04)	(6.44)
13F Week			-0.012			0.148
			(-0.22)			(1.57)
*OIB 1w * 13F Week*			0.050***			0.043***
			(2.99)			(2.81)
Lagged Mret		-0.389	-0.389		-0.401	-0.401
		(-0.65)	(-0.65)		(-0.75)	(-0.75)
Log MV		0.489	0.489		-0.012	-0.012
		(0.81)	(0.81)		(-0.02)	(-0.02)
BTM		0.991	0.991		0.951	0.951
		(1.44)	(1.44)		(1.52)	(1.52)
Return Volatility		-1.670*	-1.670*		-1.733**	-1.733**
		(-1.84)	(-1.84)		(-2.21)	(-2.21)
Intercept	0.081	-2.127*	-2.243**	-0.057	-1.820	-2.488
	(0.07)	(-1.84)	(-2.08)	(-0.02)	(-0.63)	(-0.90)
Observations	1,149,862	1,149,862	1,149,862	1,149,862	1,149,862	1,149,862
Adjusted R^2	0.001	0.032	0.032	0.001	0.031	0.031

Table 4 Cont'd.

Panel B: Longer holding period: Buy and hold returns for the next 90 trading days

	Abnormal return [1,90]			*Raw return [1,90]*		
	(1)	(2)	(3)	(4)	(5)	(6)
OIB 1w	0.834***	0.732***	0.660***	0.754***	0.667***	0.603***
	(5.43)	(5.66)	(5.24)	(5.57)	(5.74)	(5.35)
13F Week			-0.056			0.014
			(-1.00)			(0.11)
*OIB 1w * 13F Week*			0.040***			0.036**
			(2.64)			(2.55)
Lagged Mret		-0.330	-0.330		-0.277	-0.277
		(-0.57)	(-0.57)		(-0.54)	(-0.54)
Log MV		-0.353	-0.353		-1.419***	-1.419***
		(-0.69)	(-0.69)		(-2.76)	(-2.76)
BTM		0.831	0.831		0.969	0.969
		(1.02)	(1.02)		(1.29)	(1.29)
Return Volatility		-1.648	-1.648		-2.015**	-2.015**
		(-1.62)	(-1.62)		(-2.36)	(-2.36)
Intercept	0.169	-4.123***	-4.051***	0.164	-3.388	-3.553
	(0.12)	(-3.14)	(-3.35)	(0.04)	(-0.98)	(-1.10)
Observations	1,149,862	1,149,862	1,149,862	1,149,862	1,149,862	1,149,862
Adjusted R^2	0.001	0.028	0.028	0.001	0.026	0.026

Table 5: Price discovery effects

Panel A of this table reports coefficient estimates from the following panel regression:

$$CAR[-1,+1]_{it} = \beta_1 * SUE_{it} + \beta_2 * OIB1w_{it} + \beta_3 * SUE_{it} * OIB1w_{it} + \beta_4 * Inst\ Buys_{it} + Controls + Firm\ FE + Year\text{-}Quarter\ FE + \varepsilon_{it}$$

In Panel B, Retail Order Imbalance is the retail order imbalance in the 5-day period around the 13F deadline day. Price Adjustment is the fraction of future 60-day returns realized in the 5-day period around the 13F deadline day. All specifications include firm and year-quarter fixed effects and standard errors are clustered by earnings announcement date. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Price discovery of upcoming earnings news

	(1)	(2)	(3)	(4)
SUE	1.478***	2.500***	1.478***	2.488***
	(5.85)	(6.47)	(5.86)	(5.63)
OIB 1w	1.033***	1.055***	1.026***	1.048***
	(2.61)	(2.67)	(2.59)	(2.66)
*SUE * OIB 1w*	-0.799*	-0.818*	-0.791*	-0.810*
	(-1.73)	(-1.91)	(-1.71)	(-1.89)
Inst Buys			0.483	0.477
			(1.08)	(1.08)
Log MV	-1.854***	-1.886***	-1.903***	-1.934***
	(-4.44)	(-4.44)	(-4.49)	(-4.49)
BTM	-0.272	-0.296	-0.266	-0.289
	(-1.10)	(-1.19)	(-1.08)	(-1.16)
Share Turnover	-0.680***	-0.658***	-0.713***	-0.692***
	(-3.34)	(-3.22)	(-3.49)	(-3.37)
Log # Analysts	-0.391	-0.380	-0.391	-0.380
	(-1.36)	(-1.34)	(-1.36)	(-1.34)
Beta	0.092	0.075	0.094	0.076
	(0.44)	(0.36)	(0.45)	(0.36)
Std SUE	-0.052	-0.172	-0.055	-0.173
	(-0.18)	(-0.60)	(-0.19)	(-0.60)
Log Firm Age	-0.220	-0.174	-0.207	-0.161
	(-0.32)	(-0.25)	(-0.30)	(-0.23)
Q4 Indicator	2.354	2.569	2.338	2.559
	(1.25)	(1.33)	(1.24)	(1.33)
EA Day of Quarter	0.071	0.068	0.064	0.061
	(0.28)	(0.27)	(0.25)	(0.24)
CAR[-2,-62]	-0.081	-0.080	-0.087	-0.086
	(-0.51)	(-0.51)	(-0.55)	(-0.55)
Intercept	-0.538	-0.571	-0.760	-0.790
	(-0.99)	(-1.06)	(-1.30)	(-1.35)
*SUE * Controls*	No	Yes	No	Yes
Observations	8,348	8,348	8,348	8,348
Adjusted R^2	0.087	0.090	0.087	0.090

Table 5 Cont'd.

Panel B: Price discovery of institutional first buys

Retail Order Imbalance	Price Adjustment
Lowest Tercile	8.1%
Highest Tercile	11.2%
Difference (High - Low)	3.1%**

Table 6: Alternative explanation: Earnings channel

This table reports coefficient estimates from the following panel regression:

$$OIB\ 1w_{it} = \beta_1 * Inst\ Buys_{it} + \beta_2 * Lagged\ Mret_{it} + \beta_3 * Log\ MV_{it} + \beta_4 * Return\ Volatility + Firm\ FE + Year\text{-}Quarter\ FE + \varepsilon_{it},$$

where OIB $1w_{it}$ is the retail order imbalance at the one week around 13F deadline day (day 45 of the quarter), computed by aggregating daily retail order imbalances ((buy-sell)/shares outstanding). Inst $Buys_{it}$ is the institutional first buys, computed as the number of shares of the stock institutions bought as initial purchases (first buys), scaled by the outstanding number of shares, disclosed in the same period as OIB $1w_{it}$. Lagged $Mret_{it}$ is the raw stock returns over the previous month of the first trading period (i.e. days 9-38 of the quarter). Log MV_{it} is the log of firm's market capitalization, computed at the previous quarter-end. Return Volatility is the standard deviation of the raw stock returns over the previous month. SUE_{it} is the standardized unexpected earnings, defined as the actual earnings minus the most recent median analyst consensus forecast, scaled by the end of quarter stock price. Lagged SUE_{it} is SUE from the prior quarter. The sample period is January 2007-December 2017. All specifications include firm and year-quarter fixed effects and standard errors are clustered by firm. The *t*-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	13F period before earnings are announced		*13F period after earnings are announced*	
	(1)	(2)	(3)	(4)
Inst Buys	1.461*	2.005**	1.102**	1.284**
	(1.89)	(2.31)	(2.10)	(2.28)
Lagged Mret		-4.095***		-2.812***
		(-3.12)		(-4.57)
Log MV		0.303		2.034
		(0.07)		(0.88)
Return Volatility		6.636***		4.098***
		(3.64)		(4.32)
Lagged SUE		-0.952		-0.875
		(-0.82)		(-1.30)
SUE				-0.116
				(-0.19)
Intercept	0.237	2.457	4.878*	8.389**
	(0.07)	(0.65)	(1.68)	(2.50)
Observations	24,036	18,336	80,363	69,136
Adjusted R^2	0.016	0.036	0.037	0.041

Table 7: Falsification tests

This table reports coefficient estimates from the following panel regression:

$$OIB_{it} = \beta_1 * Inst\ Buys_{it} + \beta_2 * Lagged\ Mret_{it} + \beta_3 * Log\ MV_{it} + \beta_4 * Return\ Volatility + Firm\ FE + Year\text{-}Quarter\ FE + \varepsilon_{it},$$

where OIB_{it} is the retail order imbalance in percentile at different periods, computed by aggregating daily retail order imbalances ((buy-sell)/shares outstanding). Inst $Buys_{it}$ is the institutional first buys, computed as the number of shares of the stock institutions bought as initial purchases (first buys), scaled by the outstanding number of shares, disclosed at different periods than OIB_{it}. Lagged $Mret_{it}$ is the raw stock returns over the previous month of the first trading period (i.e. days 9-38 of the quarter). Log MV_{it} is the log of firm's market capitalization, computed at the previous quarter-end. Return Volatility is the standard deviation of the raw stock returns over the previous month. The sample period is January 2007-December 2017. All specifications include firm and year-quarter fixed effects and standard errors are clustered by firm. The *t*-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable:	*OIB Current Quarter Days [1-38]*		*OIB Current Quarter Days [1-38]*		*OIB Current Quarter One Week*	
Period around mid-quarter:	*Inst Buys Current Quarter Two weeks*		*Inst Buys Current Quarter One week*		*Inst Buys Next Quarter One week*	
	(1)	(2)	(3)	(4)	(5)	(6)
Inst Buys	-0.170	0.094	-0.117	0.125	0.272	0.105
	(-0.38)	(0.21)	(-0.26)	(0.27)	(0.62)	(0.24)
Lagged Mret		-5.711***		-5.712***		0.123
		(-11.86)		(-11.86)		(0.28)
Log MV		-3.421*		-3.427*		0.795
		(-1.81)		(-1.81)		(0.46)
Return Volatility		4.985***		4.983***		2.959***
		(7.09)		(7.09)		(4.42)
Intercept	0.808	3.314	0.801	3.304	3.871*	4.849**
	(0.39)	(1.60)	(0.39)	(1.59)	(1.88)	(2.33)
Observations	109,213	109,213	109,213	109,213	109,213	109,213
Adjusted R^2	0.044	0.048	0.044	0.048	0.027	0.028

Table 8: Individual investors' mimicking of last sells of 13F institutions

This table reports coefficient estimates from the following panel regression:

$$OIB_{it} = \beta_1 * Inst\ Sells_{it} + \beta_2 * Lagged\ Mret_{it} + \beta_3 * Log\ MV_{it} + \beta_4 * Return\ Volatility + Firm\ FE + Year\text{-}Quarter\ FE + \varepsilon_{it},$$

where OIB_{it} is the retail order imbalance in percentile at different periods around 13F deadline day (day 45 of the quarter), computed by aggregating daily retail order imbalances ((buy-sell)/shares outstanding). In columns 1-2 (3-4), aggregation period is two weeks (one week) around the deadline day. In columns 5 and 6, aggregation period is just the three trading days centered on the deadline day. Inst Sells $_{it}$ is the institutional last sells, computed as the number of shares of the stock institutions sold as a complete liquidation of position, scaled by the outstanding number of shares, disclosed in the same period as OIB_{it}. Lagged $Mret_{it}$ is the raw stock returns over the previous month of the first trading period (i.e. days 9-38 of the quarter). Log MV_{it} is the log of firm's market capitalization, computed at the previous quarter-end. Return Volatility is the standard deviation of the raw stock returns over the previous month. The sample period is January 2007-December 2017. All specifications include firm and year-quarter fixed effects and standard errors are clustered by firm. The *t*-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Period around mid-quarter:	*Two weeks*		*One week*		*Three days*	
	(1)	(2)	(3)	(4)	(5)	(6)
Inst Sells	-0.623	-0.598	1.220***	1.172***	0.880**	0.821**
	(-1.50)	(-1.45)	(2.95)	(2.84)	(2.18)	(2.04)
Lagged Mret		-5.182***		-2.966***		-2.919***
		(-10.81)		(-6.16)		(-6.17)
Log MV		-0.959		-0.660		0.457
		(-0.54)		(-0.38)		(0.27)
Return Volatility		4.865***		3.280***		2.225***
		(7.13)		(4.91)		(3.36)
Intercept	3.393*	6.929***	3.924*	6.171***	2.963	4.681**
	(1.82)	(3.66)	(1.90)	(2.95)	(1.40)	(2.18)
Observations	109,230	109,230	109,230	109,230	109,230	109,230
Adjusted R^2	0.031	0.033	0.027	0.028	0.023	0.023

Table 9: Individual investors' mimicking of trades of insiders

This table reports coefficient estimates from the following panel regression:

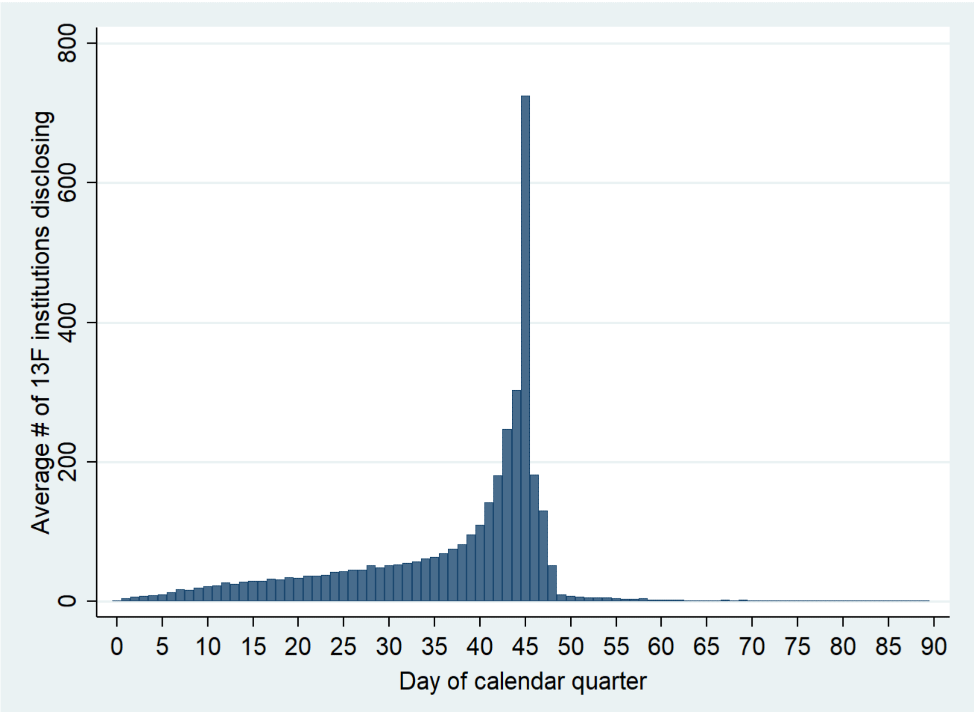
$$OIB\ 2d_{it} = \beta_1 * Insider\ Buys_{it} + \beta_2 * Lagged\ Mret_{it} + \beta_3 * Log\ MV_{it} + \beta_4 * Return\ Volatility + Firm\ FE + Year\text{-}Month\ FE + \varepsilon_{it},$$

where OIB 2d$_{it}$ is the retail order imbalance for the event window, i.e. two days, computed by aggregating daily retail order imbalances (retail bought minus retail sold, scaled by the outstanding number of shares) of the event day and the following day. Insider Buys$_{it}$ is computed as the number of shares purchased by the insider, scaled by the outstanding number of shares. Definitions of insider types are provided in Section 4.8. All other variables are defined in the Appendix. The sample period is January 2017-December 2017. All specifications include firm and year-month fixed effects and standard errors are clustered by firm. The *t*-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	All insiders	*Opportunistic locals*	*Routine locals*	*Routine insiders*	*Top 5 insiders*	*Non-Top 5 insiders*	*Non-exec directors*	*Other non-top 5 insiders*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Insider Buys	0.618**	1.057*	0.087	-0.033	-0.026	0.776**	2.196***	0.536
	(2.17)	(1.73)	(0.13)	(-0.06)	(-0.07)	(2.10)	(3.11)	(1.25)
Lagged Mret	-3.429***	-3.086***	-4.665***	-4.166***	-2.502***	-3.683***	-3.892***	-3.485***
	(-7.09)	(-3.42)	(-5.83)	(-5.83)	(-4.20)	(-6.97)	(-5.38)	(-5.41)
Log MV	-4.457***	-10.326***	-6.574**	-4.229*	-2.520	-5.344***	-5.780**	-4.513*
	(-2.77)	(-2.72)	(-2.01)	(-1.66)	(-1.41)	(-3.00)	(-2.57)	(-1.93)
Return Volatility	6.397***	3.752***	8.630***	7.784***	6.055***	6.465***	6.512***	6.360***
	(9.07)	(2.86)	(5.60)	(6.01)	(6.80)	(8.54)	(6.30)	(6.87)
Intercept	6.323***	-6.958	7.929*	5.075**	3.439	7.368***	8.609***	4.465*
	(3.89)	(-1.12)	(1.82)	(2.06)	(0.92)	(4.04)	(3.30)	(1.70)
Observations	552,704	87,648	126,401	181,739	118,241	434,463	209,829	224,634
Adjusted R^2	0.058	0.068	0.061	0.052	0.060	0.063	0.097	0.071

Figure 1. 13F disclosure timing and volume

The figure at the top plots the average number of 13F institutions disclosing per each day of the calendar quarter. Similarly, the bottom figure plots the average dollar volume of their first buys (in $ billions) per each day of the calendar quarter. Day 45 is the deadline day.



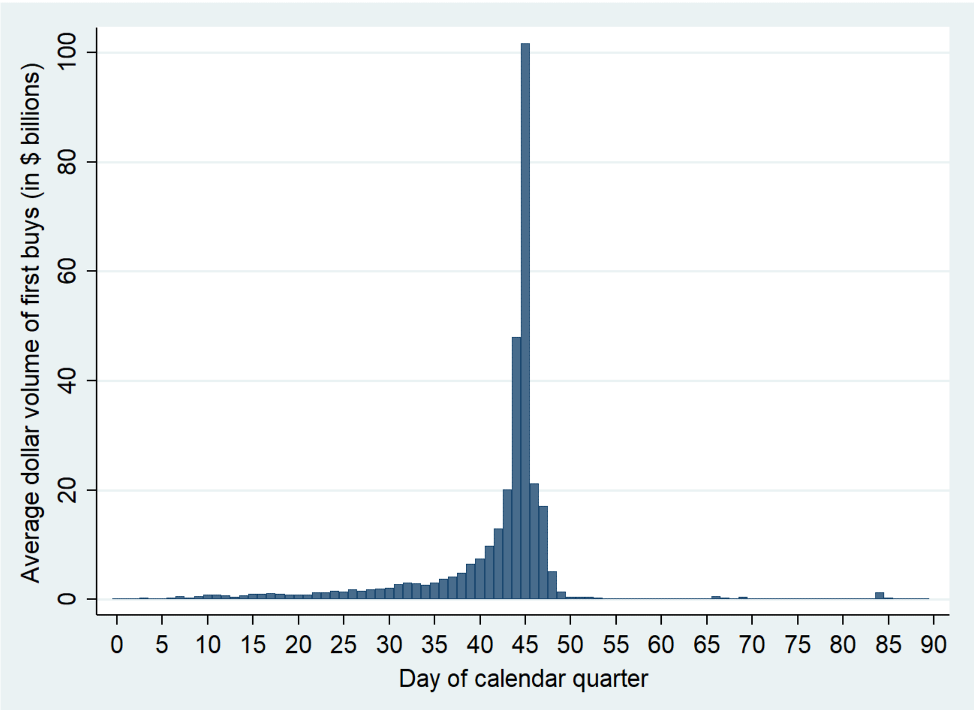


Figure 2. Timeline of examined 13F disclosure windows

This figure illustrates a timeline of the accumulation windows used in the main analyses. First buys of institutions revealed in 13F filings and retail trades are both accumulated through these three windows.

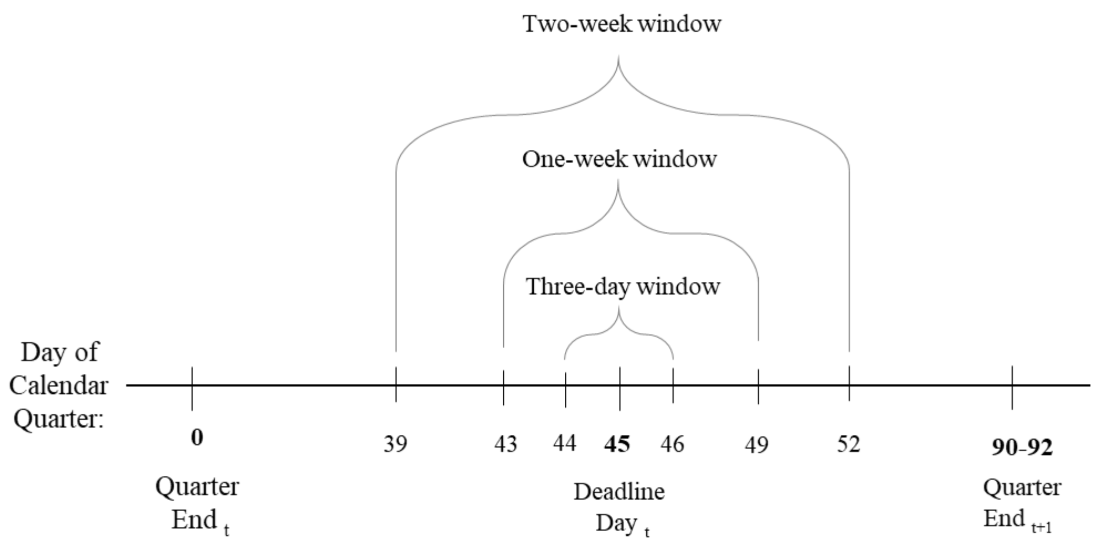
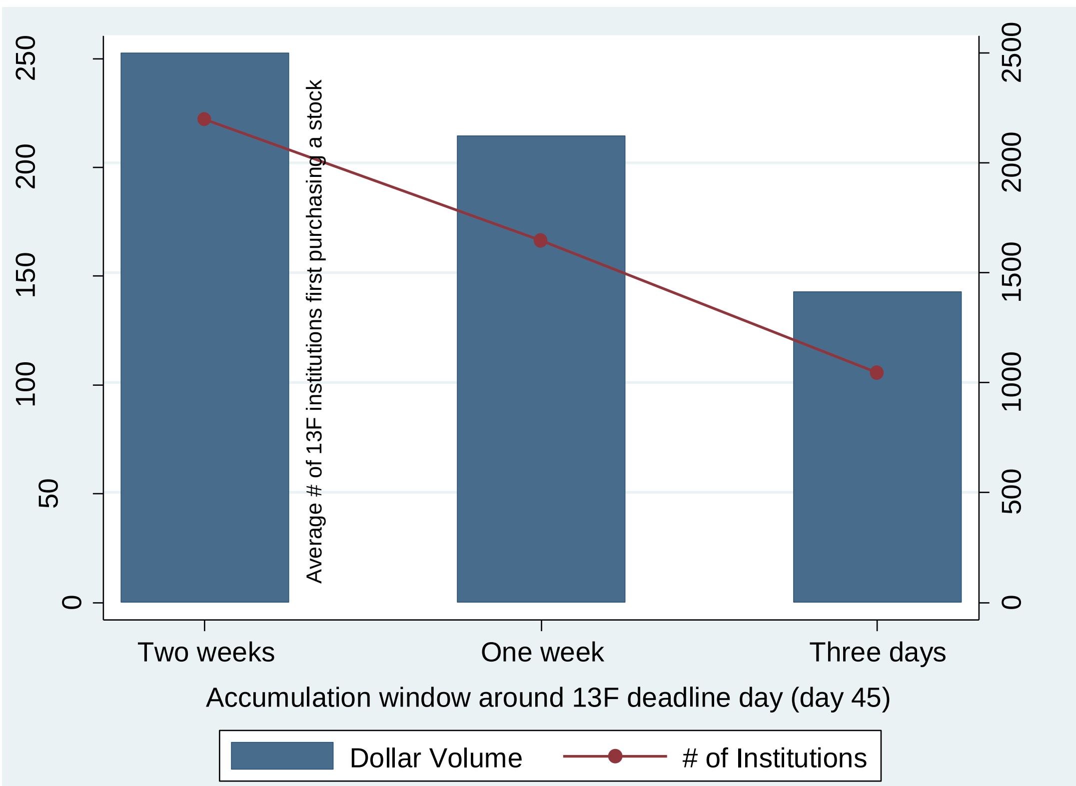


Figure 3. First buys around 13F disclosure windows

This figure plots the average dollar volume of first buys (in $ billions) and the average number of 13F institutions, at different accumulation windows around 13F deadline day (day 45 of the calendar quarter).



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