Can Retail Investors Learn from Insiders?

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Abstract

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JEL Classification: G11, G12, G14.

Keywords: Retail order flow; Insider trading; Price discovery; Return predictability; Informed investors.

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Abstract

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1 Introduction

Facilitating price discovery in financial markets is an important function that market participants perform. The roles of these participants differ across trader types and the technologies that they control. While individually important, the interactions among different players are vital for the flow of information into prices. In this paper, we study how two special groups of traders, corporate insiders and retail traders, interact with each other and help improve the price discovery process.

Corporate insiders, by definition, have access to firm's private information ahead of other investors.[1] Previous studies have documented the informational role of insider trading. For example, Lakonishok and Lee (2001) find that insiders can predict stock returns in the cross-section. Several other papers also show that insiders trade on private information and earn significant returns.[2] In addition, Cohen, Malloy, and Pomorski (2012) separate insider trades into "opportunistic" trades and "routine" trades, and show that the return predictability mostly come from the "opportunistic" trades. The informational role of retail investors is less clear. Earlier studies tend to show retail investors as a group are uninformed and irrational.[3] Some recent papers, on the other hand, point out that retail investors are informed and earn positive abnormal returns.[4]

As insider opportunistic trading is most likely information driven, to the extent that retail trading predicts stock returns, the interaction between insiders and retail investors provides a useful setting in disentangling the sources of the return predictability, which is often difficult to do. For example, if retail investors trade against insiders, it is likely that

[1] The Securities and Exchange Act of 1934 defines insiders as officers, directors, and shareholders of 10% or more of any equity class of securities.

[2] For example, see Jaffe (1974), Seyhun (1986), Rozeff and Zaman (1988), Lin and Howe (1990), Bettis, Vickrey, and Vickrey (1997), Seyhun (1998), Lakonishok and Lee (2001), Jeng, Metrick, and Zeckhauser (2003), Marin and Olivier (2008), Jagolinzer (2009).

[3] Barber and Odean (2000) use household trading data and document that net returns earned by households are poor. Barber, Odean, and Zhu (2009) show that retail investor buying (selling) push prices too high (low) leading to subsequent reversal.

[4] For example, Kaniel, Saar, and Titman (2008) document positive excess returns in the month following intense individual buying and negative excess returns following intense individual selling. Boehmer, Jones, Zhang, and Zhang (2021) propose a novel method to separate out retail orders from TAQ, and they find that retail investors are well informed about firm news and are likely to hold private information. Other papers that document retail investors' informed trading are Kaniel, Liu, Saar, and Titman (2012), Kelley and Tetlock (2013), Barrot, Kaniel, and Sraer (2016), Fong, Gallagher, and Lee (2014) and etc.

some of these traders are providing liquidity to insiders and may profit from that in the short term. If they follow insider trades, they are demanding liquidity, and their trading is likely driven by information content revealed from the insider trades. Examination of these potential sources of trading motivation and the corresponding price formation process would help us understand how information is impounded into stock prices.

In this paper, we study the joint trading patterns of insiders and retail investors and their impact on future stock returns. We then examine possible sources of any observed return predictability of these trades. Unlike most of the retail trading studies that use proprietary data from a few brokers, we follow Boehmer et al. (2021) to filter out daily retail trades from TAQ trade dataset. To identify insider trades, we use Thomson Reuters Insiders data (Form 4) and extract insider open market purchases and sales and examine the trading and stock return patterns at the daily and weekly level for both insiders and retail investors.

Consistent with Boehmer et al. (2021), retail order imbalance is negative in general outside the insider trading event window (between the insider trade date and one day after the report date). Retail investors, however, tend to buy during the event window the stocks that insiders have purchased, and sell those that insider have sold, more than they usually sell. A Granger-type causality test indicates that retail investors follow informed insider purchases, and not the other way round. The evidence suggests that at least some retail investors are able to identify and follow insider trades in a timely fashion. Moreover, retail investors do not blindly follow insider trades. We follow Cohen, Malloy, and Pomorski (2012) to separate insider trades into "opportunistic" trades and "routine" trades. We find that retail investors tend to follow opportunistic insider purchases, but not routine insider purchases, during the event window. Further analysis suggests that retail investors keep buying stocks with opportunistic insider purchase for up to four quarters. To the extent that insider "opportunistic" trades reflect insider's private information, at least retail investors seem to be able to identify and learn from the actual informed trades, and act quickly.

One possible channel of learning is through retail investors' brokers. Li, Mukherjee, and Sen (2021) provide evidence that mutual fund managers gain informational advantage from affiliated brokers of corporate insiders. McLean, Pontiff, and Reilly (2020) argue that analysts and brokers at large investment banks also have incentives to "tip" retail investors.

As a result, retail investors could learn about insider trades through their informed brokers. Moreover, with the advancement in technology and the abundance information, savvy retail investors can monitor and research about insider trades on their own. Indeed, we find an increase in the abnormal retail downloads of the insider trading filing Form 4 in the EDGAR database. Higher abnormal retail downloads during the event window are also associated with more retail buys in the following days. This evidence is most significant for stocks with opportunistic insider purchases.

There is however no clear distinction of retail investor trading pattern corresponding to opportunistic and routine insider sales. This result is not surprising, as the existing literature suggests that insider sales tend to be driven by liquidity and diversification reasons, whereas insider purchases are regarded as strong positive signals in stock values.[5] We hence focus on retail order flow around insider purchase window from now on.

While our results are consistent with retail investors following insider purchases because they learn from informed trades by insiders, it is however possible that insider trades simply increase the market attention to the stock. As investors have limited attention, the increased exposure of the stock prompts retail investors to buy more shares. Barber and Odean (2008) show that individual investors are net-buyers of attention-grabbing stocks. Da, Engelberg, and Gao (2011) further use Google search volume to proxy for the abnormal attention of retail investors, and they show transitory price pressures on those attention-grabbing stocks.[6] We follow Da, Engelberg, and Gao (2011) and manually collect the weekly Google Search Volume Index (SVI) to measure retail investor attention. We then examine how retail investors follow insider purchase for stocks with high abnormal SVI (ASVI) and low ASVI separately. While high ASVI stocks do experience larger retail investors trading volume in the insider trading event window, attention is not a driving force for retail investors to follow insider trades. When insiders buy opportunistically, retail investors tend to follow them, regardless of the level the investor attention. We also follow Barber and Odean (2008) and use abnormal trading volume to proxy for general investor attention. The results are similar: investor

[5] Jeng, Metrick, and Zeckhauser (2003) find weak evidence on the profitability of insider sales. They find that insider purchase earn abnormal returns of more than 6% per year, while insider sales do not earn significant abnormal returns.

[6] Other papers such as Gervais, Kaniel, and Mingelgrin (2002) and Ben-Rephael, Da, and Israelsen (2017) also examine the investor attention effect.

attention is positively correlated with retail investors' purchasing behavior, but it is not the main reason why retail investors follow insider trades.

Another possibility is that retail investors and corporate insiders make their trading based on the same set of information around the same time. For example, Kaniel et al. (2012) show that both purchases and sales of stocks by retail investors before the earnings announcements can predict returns after the announcements. To examine the effect of earnings as potential common source of information, we repeat the earlier analysis separately for stocks with or without earnings announcements within one month after the insider trading window. For those stocks with near future earnings announcements, we also examine those with positive and negative SUEs separately. The results show that retail investors follow opportunistic insider purchases regardless if there are earnings announcements. For the subsample with near future earnings announcements however, we do find that retail investors follow insider purchase more aggressively for stocks with positive future SUE than those with negative SUE, which is consistent with Kaniel et al. (2012). Taken together, these results suggest that some retail investors might trade in the same direction as the insiders because they share common information about future earnings. However, the near future earnings cannot be a driving force as retail investors still follow opportunistic insider purchase for the vast majority of the cases where there is no near future earnings announcements.

We also test analysts forecast revisions and recommendation updates as potential sources of common information. The results are consistent with those of the earnings announcements. Retail investors actively follow opportunistic insider purchases, regardless of whether there is recommendation upgrade/downgrade, or forecast up/down revision. If anything, when retail investors follow opportunistic insider purchases more aggressively, it is more likely to have near-future analyst downward revisions/recommendation downgrades than upward revisions/recommendation upwards. Collectively, these findings suggest that retail investors follow insider trades not simply because these trades catch their attention or because they share the same information with insiders. It is likely that they follow insider trades because of the private information content revealed by these trades.

If opportunistic insider trading does reveal private information that retail investors can identify, trading alongside insiders by retail investors should help expedite the price discovery process for the underlying stock. We test this hypothesis by examining the future returns of stocks traded by retail investors following insider buying. First, we provide out-of-sample evidence as in Cohen, Malloy, and Pomorski (2012) that the opportunistic trades by insiders earn higher returns than the routine trades. More importantly, for stocks with opportunistic insider purchases, our event-week portfolio test shows that the returns on those stocks that retail investors buy have higher market-adjusted returns than those that retail investors sell. Stocks with positive retail order flow earn abnormal return that is 10 basis points (t-stat = 3.55) higher next week than those with negative retail order flow. The cumulative return differences between these two groups remain significant for up to 18 weeks with no long-term return reversals. We also conduct calendar-week portfolio analysis. For each week, we form a long/short portfolio that longs the stocks with opportunistic insider purchases that are bought by retail investors, and shorts those that are sold by retail investors. The excess return on the long/short portfolio earns significantly positive CAPM and the Carhart four-factor alphas.

Next, we conduct predictive panel regressions of next-week stock returns on a dummy variable (Follow_Oppbuy) that equals one if retail investors choose to buy the stocks with opportunistic insider purchases during the same week. The coefficient on Follow_Oppbuy is positive and significant. Besides examining the sub-sample of stocks with opportunistic insider purchases, we also regress next-week stock returns on an opportunistic insider purchase dummy, a retail purchase dummy, an interaction term of the two, and a number of control variables in the full-sample. Importantly, controlling for insider purchases and retail purchases, the coefficient on the interaction term is positive and highly significant. The results of both sub-sample regression and full-sample regression are consistent with the hypothesis that retail investors learn from the opportunistic insider purchases, and their trading helps speed up price discovery by impounding the private information revealed by the insider trades into stock prices faster. These results pass a number of robustness tests. Moreover, we show that for stocks with opportunistic insider purchases, return differences between stocks retail investors purchase and those they sell are significantly larger for stocks with greater information symmetry (smaller stocks, stocks with higher idiosyncratic volatility and stocks with higher Amihud illiquidity), further supporting the information hypothesis.

Interestingly, when retail investors sell the stocks that insider have purchased, those stocks still have higher future returns, albeit not as high as those that bought by retail investors. This suggests that retail investors do not seem to have superior information during the insider trading window on top of what is possessed by the insiders. When they can learn from insider trades, they improve price discovery; when they fail to do so, they only delay the process.

The return predictability of retail trading is not driven by the liquidity provision. Because retail investors and insiders are in the same side of the trade during the event window, by definition retail investors are not providing liquidity to insiders. However, it is possible that they provide liquidity to other market participants who trade against them, and make profits from liquidity provision. To formally examine the liquidity provision hypothesis, we follow Boehmer et al. (2021) and decompose the retail trades into three components: one attributed to price pressure, one to liquidity provision, and the rest to information. We then repeat the panel regression analysis. The results show that only the coefficient on the information component is highly significant, and those on liquidity provision and temporary price pressure are statistically insignificant.

To further examine the efficiency gain of the retail trading following opportunistic insider purchase, we construct two additional commonly used price efficiency measures: the Lo and MacKinlay (1988) variance ratio and the Hou and Moskowitz (2005) price delay measure.[7] We repeat the above panel regressions, except that we replace the future returns with the absolute value of one minus the variance ratio and the price delay measure as the dependent variables. We find strong evidence of gain in efficiency measured by the variance ratio, but not by the price delay measure. Since the variance ratio mostly measures firm level information while the price delay measures the speed of the market information incorporated into prices, our tests suggest that the trading of retail investors helps impound the firm specific information into the stock prices, but not the market level information.

Several recent papers examine interaction between insider trading and retail trading. Mansi, Peng, Qi, and Shi (2021) show significant increase in insider opportunistic selling

[7] For other papers that use these measures, see Barnea (1974), Boehmer and Kelley (2009), and Boehmer and Wu (2013).

(buying) following increase (decrease) in retail attention. Stotz and Georgi (2012) obtain 1-year retail trades from a retail broker in Germany. They provide evidence of retail investors copying the trades of insiders, although retail investors' copying behavior yields insignificant future abnormal returns. Using NYSE data, Chung (2020) argues that a substantial portion of retail trading around the insider trading window is the trading by insiders themselves. Neither paper differentiates opportunistic insider trades from routine trades. As we explain later, retail trading in our sample is in the OTC market. With our identification methodology, insider trading is mostly excluded from the retail trading sample by construction. Removing the small amount of potential insider transactions do not affect the empirical results. Unlike the above papers, we show that retail investors not only able to follow opportunistic insider trades, but their trading can predict future returns beyond insider trading.

More generally, our paper contributes to the understanding of the interaction among different market players in the process of price discovery. While extensive studies have been done on insiders, institutional/retail investors, as well as short sellers, relatively few studies analyze the effects that these trader types have on other types and on how they interact with each other. Notably, Massa, Qian, Xu, and Zhang (2015) examine how insiders' strategy changes when they need to compete with short sellers. Kelley and Tetlock (2013) control for insider sales when examining the retail shorting activity. These studies focus on the interaction between insiders and short sellers in the presence of negative information. Our paper examines the combined effect of insiders and retail investors, who are traditionally not seen as informed players. The results indicate that retail investors can be informed, by showing that they are able to identify the *positive* private information revealed by insider trades. Our paper is also related to Sias and Whidbee (2010), who show an inverse relation between insider trading and institutional demand during the same quarter and over the previous quarter. By comparison, we use comprehensive TAQ-based daily retail trading data, and show that retail investors trade alongside insiders during the insider trading window. Moreover, we show that retail investors follow insiders not for liquidity reasons, but to learn about insiders' private information from their opportunistic trades. By following insiders' informed trades, retail investors improve the price discovery process of the underlying stocks.

The rest of our paper is organized as follows. Section 2 provides the data description and summary statistics. Section 3 examines the trading pattern of retail investors around insider trades. Section 4 further explores the information content of retail trades around insider trades. Section 5 conducts additional robustness checks. Section 6 concludes the paper.

2 Data and Sample Construction

In this section we first illustrate various sources of the data used in our tests, and we then present the sample construction and summary statistics.

2.1 Retail Trading Data

Our main data on retail investor trades come from TAQ trade dataset over the period from January 1, 2010 to December 31, 2018. According to Boehmer, Jones, Zhang, and Zhang (2021), retail orders that are internalized or executed by wholesalers are given a small amount of price improvement relative to the National Best Bid or Offer (NBBO). We follow their paper's price improvement measures to isolate retail investors' marketable orders from institutional orders. Specifically, we identify a transaction as a retail buy if the subpenny price is between 60 and 100 basis points, and identify a retail sell if the subpenny price is between 0 and 40 basis points. We then aggregate retail buy volume, the number of retail buy trades, retail sell volume, and the number of retail sell trades for each stock on each trading day.[8] [9]

To construct retail investors' directional trades for each stock on each trading day, we follow Boehmer et al. (2021) and define the order imbalance in terms of both the trading volume $oibvol_{i,t}$ and the number of trades $oibtrd_{i,t}$, as the following:

$$oibvol_{i,t} = \frac{indbvol_{i,t} - indsvol_{i,t}}{indbvol_{i,t} + indsvol_{i,t}} \tag{1}$$

[8] The sample period does not include years before 2010 because the subpenny trade practice only stabilizes after 2009. Also, because the SEC's tick size pilot program (TSPP) from 2016 to 2018 might affect the practice of subpenny price improvements unevenly in the cross section, we 1) exclude the TSPP period in the sample and re-run our main tests, and 2) construct TSPP as a dummy variable and interact it with our main variables in panel regressions. We find that the results during the pilot period is not materially different from the earlier sample. We omit the tables for brevity.

[9] For more details, refer to Boehmer et al. (2021).

$$oibtrd_{i,t} = \frac{indbtrd_{i,t} - indstrd_{i,t}}{indbtrd_{i,t} + indstrd_{i,t}} \quad (2)$$

where $indbvol_{i,t}$ ($indsvol_{i,t}$) is the number of shares of stock i bought (sold) by retail investors on day t, and $indbtrd_{i,t}$ ($indstrd_{i,t}$) is the number of buy (sell) trades of stock i on day t.

2.2 Insider Trading Data

We obtain insider trading data from the Thomson Reuters Insider Filing database. According to the Securities and Exchange Act of 1934, open market trades by corporate insiders should be reported to the SEC within 10 days after the end of the month in which they took place. In 2002, the ten-day deadline was changed to a two-day deadline instead. However, as shown in Table A1, about 6.3% of insiders report their trading after the 2-day deadline. In our sample, we only use insider trades that are reported within the 2-day deadline.[10]

Corporate insiders from the database include company officers, directors, and beneficial owners of more than 10% of a company's stock. We extract the SEC's Form 4 data during the sample period from January 2010 to December 2018. We focus on open market purchases and sales by insiders, and exclude option exercises and private transactions.

Our data include both the transaction date and the SEC filing date (when the insider trading information is available to the general public). Table A2 shows that retail order imbalance spikes up from the insider trading date to the filing date. In our main analysis, we define the insider trading event window as the days within the insider trading date and one day after the filing date, including both ends.[11]

Chung (2020) provides one potential explanation for the change of retail trading imbalance around the insider trading events – a large portion of these retail trading is actually the trading by insiders themselves. We rule out this explanation in our setting. While Chung (2020) obtains retail trading volume from NYSE, our sample includes only off-exchange retail trades. Moreover, in our sample, 94.81% (86.58%) of the open market purchases (sales)

[10] Our results remain consistent when we include trades with reporting lags larger than 2 business days.

[11] We include one day after the filing date in the event window as there may be time lag of investors' responses. For robustness, we also examine our main tests when defining the event window that ends at the filing date, or ends at two days after the filing date, and the results remain consistent. The tables are omitted for brevity.

by insiders cannot be attributed to retail trading. The reason is that either the transaction price of an insider trading does not satisfy the price improvement algorithm, or the trading volume of an insider transaction already exceeds that of daily retail trading in total. For the remaining small portion of insider transactions that may be counted as retail trading, we remove them from our sample and the empirical results are not affected.

2.3 Other Types of Data

The accounting variables and the earnings announcement data are obtained from Compustat. We obtain analyst forecast data from the Institutional Brokers' Estimate System (IBES), and data on institutional holdings from Thomson Reuters (13F).

Additionally, we download IP search volume data from the SEC EDGAR log file database, which include internet search traffic for EDGAR filings.[12] Each log entry includes the IP address of the requesting user, time stamp of the request, Central Index Key (CIK) of the company that filed the form, as well as the accession number that identifies the specific filing type. Following Drake, Roulstone, and Thornock (2015), we download the Master Index files from the SEC website and then match them with the log files based on the accession number to obtain both the filing type and filing date for each entry. As we are interested in the insider filing type, we only keep those entries with form 4 filings. We then exclude the records with index specifications to remove redundancies. Furthermore, we follow Drake, Roulstone, and Thornock (2015) and Chi and Shanthikumar (2018) to remove entries where the IP address has more than five requests per 60-second interval or more than 1,000 requests per day, so that the remaining records are likely to be employed by retail investors, who usually would not use automated web crawler programs to search and download files. As a result, for each stock on each day, we count the number of unique IP addresses searching for Form 4 filings and then subtract its prior sixty-day average value to obtain retail abnormal EDGAR search (A_Search).

We also obtain Google's Search Volume Index (SVI) and construct abnormal retail investor attention, similar to Da, Engelberg, and Gao (2011). We manually collect the weekly

[12] As the EDGAR log files cover from February 14, 2003 through June 30, 2017, our analysis with EDGAR search ends in mid-2017.

Search Volume Index for each stock ticker using a web-scraping technique, and extract stock tickers (TICKER) that appear in our main sample. We delete tickers with a generic meaning such as "ALL", "B", and "GPA" manually.[13] We collect weekly SVI from 5,524 distinct firm tickers during April 2009 through December 2018. We then merge SVI statistics with stocks in our main sample. Following Da, Engelberg, and Gao (2011), we use the abnormal search volume index (ASVI) as the proxy for the retail investor abnormal attention. We calculate ASVI as the log of SVI during the week minus the log of median SVI for the previous eight weeks. We also use the abnormal trading volume (ATT) as the proxy for general investor attention, following Barber and Odean (2008). We divide each stock's daily trading volume by its average trading volume in the previous year (252 trading days), and then take the weekly average to get ATT.

We merge our retail and insider transaction data with the stock-level characteristic variables. Our sample contains common stocks (CRSP share codes 10 and 11) listed on NYSE, AMEX, and NASDAQ. We exclude stocks with price less than 1 dollar. We winsorize all the continuous variables at 1% and 99% level. The sample period is from January 1, 2010 to December 31, 2018.

2.4 Summary Statistics

Table 1 shows summary statistics for the sample. We report firm characteristics for the retail trading sample as well as the insider trading sample. We divide the sample into stocks with different types of insider trades, and then further divide each sub-sample based on whether retail investors trade on the same side with insiders or on the opposite side.

[Table 1 here]

Panel A of Table 1 presents summary statistics for stocks traded by insiders and retail investors. We report the main variables in weekly frequency. For retail order imbalance measures, the mean and median values for both the volume imbalance (*oibvol*) and the trade imbalance (*oibtrd*) are negative, with the mean of *oibvol* -0.021 and the median -0.013,

[13] These generic-meaning tickers would cause ambiguity and create more noise.

and the mean of *oibtrd* -0.016 and the median -0.004. These statistics are consistent with Boehmer et al. (2021), in which the mean retail order imbalance is also negative. Insider trades vary a lot in terms of the number of shares traded. While the weekly median of the insider buy volume is 10,000 shares and the weekly median of the insider sale is 20,000, their weekly mean values reach 233,000 and 228,000, respectively. The 75$^{\text{th}}$ percentile of both variables are 42,120 and 62,770. These figures suggest that some insiders trade with abundant blocks of shares.[14] Moreover, the number of insider purchases has a weekly average of 4.6 (times) and a weekly median of 2. The number of insider sales has a weekly average of 5.1 and a weekly median of 2.

Panel B and Panel C of Table 1 report characteristics of stocks purchased and sold by insiders, respectively. For each panel, we further group stocks into those that retail investors trade on the same side as insiders (Follow), and those that retail investors trade on the opposite side (Not-Follow). We compare stock size, book-to-market ratio, past 6-month momentum, return reversal, turnover, idiosyncratic volatility as well as investor abnormal attention for stocks in sub-samples. However, retail investors' trading decisions do not depend on specific stock characteristics. If we compare stock characteristics among insider trading sub-samples, we find that stocks insiders sell tend to have higher momentum (both past 6-month cumulative return and prior month return) than those bought by insiders. The contrarian trading pattern is consistent with prior literature (Piotroski and Roulstone, 2005; Cohen, Malloy, and Pomorski, 2012).[15]

2.5 Retail Order Flow around the Insider Trading Event Window

We define the insider trading event window as the days from the insider trading date until one day after the insider filing date. The U.S. Securities and Exchange Commission (SEC) requires that corporate insiders report their open market trades within 2 days after the trading date. This 2-day deadline has replaced the previous 10-day deadline since 2002. To rule out the effect of nearby insider trades in our event window for each stock, we cluster

[14] As these large block trades are more likely to catch attention from regulators and other investors, we expect that they contain less information. Our results are robust after removing these large block trades.

[15] In this paper, we focus on what drives retail investors' trading on the same side as insiders. Therefore, we compare stock characteristics between Follow and Not-Follow groups in each insider universe.

the adjacent insider trades (within 5 days) into one group.[16] Also, it is essential to exclude the possibility that insider trades in our sample are classified as OTC retail trading. Chung (2020) obtain NYSE retail trading volume and indicates it contains trades from insiders. However, even if we assume all the insider trades are executed by OTC wholesalers or via internalization, there are at most 4.9% of the total insider trades may be included in retail OTC volume.[17] Removing them from retail trades does not affect our main results. We report retail order imbalance within 5 trading days around the event window with Newey-West adjusted standard errors.

[Table 2 here]

Table 2 provides summary statistics of retail order imbalance around event window. Consistent with Table 1, retail order imbalance is negative for days before and after the insider purchase event window. However, during the insider trading window, the aggregate retail investors tend to buy the stocks that insiders have purchased. Specifically, Panel A shows that *oibvol* increases by 129 percent from the day before to the days in the insider purchase window, and *oibtrd* increases by 146 percent during the same period. Panel B shows that retail investors tend to sell the stocks that insiders have sold, more than they usually sell, during the event window.[18] Between the day before and during the insider sale window, *oibvol* decreases by 14 percent and *oibtrd* decreases by 5 percent.

Next, we differentiate between informed and uninformed insider trades, as in Cohen, Malloy, and Pomorski (2012). They identify insiders as either opportunistic (informed) or routine (uninformed), based on past trading patterns. Interestingly, retail investors' trades as a group are consistent with opportunistic insiders' trades, and not with routine insiders' trades. For the opportunistic insider trades, retail investor order imbalance during the event

[16] Clustering is necessary because adjacent insider trades is common in our sample, where 48.6% of the sample have adjacent insider trades. For robustness, we also employ 10-day clustering and 20-day clustering, and the results remain similar.

[17] Using the price improvement measure in Boehmer et al. (2021) to identify retail trades, we find more than 85% of the insider trades in our sample cannot be classified as retail trading. For the remaining insider trades that may be counted in retail trading, we further exclude the insider buy (sell) transactions with volume exceeding retail buy (sell) volume on the same trading day.

[18] Given the negative-skewed nature of retail order imbalance, which means retail investors sell their shares overall, we still capture a more negative retail order imbalance during the insider sale event window.

window is 0.9 percent in terms of *oibvol*, and 1.1 percent in terms of *oibtrd*, both statistically significant. For the routine insider trades, the corresponding *oibvol* is -1.5 percent and *oibtrd* -0.6 percent. These results suggest that aggregate retail investors do not blindly follow insider trades. Rather, they tend to follow informed insider trades more than they follow uninformed ones. There is no clear distinction of retail investor trading pattern for opportunistic and routine sale conditions. The result is not surprising, as most papers show that insider sales are usually driven by liquidity and diversification reasons, where insider purchases are regarded as strong positive signals in stock values. For example, Jeng, Metrick, and Zeckhauser (2003) find that insider purchases earn abnormal returns of more than 6% per year, while insider sales do not earn significant abnormal returns. Hence, from now on we focus on retail order flow around insider purchase window.

[Figure 1 here]

Figure 1 presents retail order imbalance, *oibvol* and *oibtrd*, from 20 trading days before the insider trading event window to 20 trading days after the event window. Consistent with earlier results, there is a spike for the insider purchase event window from one day before, and a decrease for the insider sale event window from one day before. During the event window, order imbalance is positive for the opportunistic purchase sample but negative for the routine purchase universe, shown in both *oibvol* and *oibtrd*. The order imbalance in the routine sample is also more volatile than that in the opportunistic sample.[19]

[Table 3 here]

Results in Table 2 suggest that retail investors learn about insider trades, especially opportunistic insider trades, and act in a timely way. While it is difficult to pin point the exact (likely multiple) channel of their learning, we examine one specific source of insider trading information that retail investors can have access to – the SEC's EDGAR database. We report the abnormal retail downloads of the insider Form 4 filing from EDGAR, as described in the earlier section. Panel A of Table 3 shows that there is a surge in the retail

[19] It could be the reason that retail investors regard routine trades as uninformative, and they tend to trade more arbitrarily than in the opportunistic sample.

downloads of Form 4 filings during the event window for insider purchases, with the average abnormal EDGAR downloads at 2.36. And this surge is entirely for stocks with opportunistic insider purchases at 2.59. The corresponding abnormal downloads for routine purchases are actually negative. The average abnormal retail downloads from EDGAR for insider sales are much smaller at 0.8, and there is no significant difference for the abnormal EDGAR downloads between opportunistic insider sales and routine sales.

Panel B of Table 3 shows the retail trading on stocks with insider trades. We sort stocks based on the ranking of the abnormal EDGAR downloads, and compare the difference in retail trading between those stocks in the top quintile of the abnormal EDGAR downloads and those in the bottom quintile. There is significant difference in retail trading between the top and the bottom quintile during the event window and 2 days after the filing date, and the difference remain positive for the next 5 trading days. For example, *oibvol* during the event window for the top EDGAR search quintile is 2.50%, while that for the bottom quintile is -1.35%. The difference between the top and the bottom quintile is 3.85%, statistically significant at the 1% level. We further make the comparison separately for stocks with opportunistic insiders buys and routine insider buys. For stocks with opportunistic insider buys, *oibvol* for the stocks in the top quintile of the abnormal EGDAR downloads during the event window is 2.30%. The difference in retail trading between the top and the bottom quintile is 2.70%, statistically significant at the 5% level. For stocks with routine insider buys, *oibvol* for the stocks in the top quintile of the abnormal EGDAR downloads during the event window is smaller at 0.6% and statistically insignificant. Overall, results in Table 3 provide direct evidence that some retail investors do learn about insider trades through EDGAR search, and downloading the insider filing forms has effect on their trading decisions.

3 Retail Trading Patterns around Insider Trades

In this section we examine the retail weekly trading pattern for stocks that insiders bought. We then examine potential sources that may explain these trading patterns.

3.1 Baseline Results

In our main empirical analysis, we use weekly-frequency data to reduce microstructure noise. We also run daily-frequency tests in the appendix and the results all remain unchanged. We employ multivariate analysis of event-week retail order imbalance on insider trading indicators. Specifically:

$$Oib_{i,t} = a + b * Ins_{i,t} + c * X_{i,t-1} + \epsilon_{i,t} \tag{3}$$

We regress stock i's retail order imbalance in week t ($\mathrm{Oib_{i,t}}$) on an insider trading dummy variable in the same week ($\mathrm{Ins_{i,t}}$), and control for other stock characteristics ($\mathrm{X_{i,t\text{-}1}}$). We use both variables (*oibvol* and *oibtrd*) as proxies for $\mathrm{Oib_{i,t}}$. $\mathrm{Ins_{i,t}}$ refers to a dummy variable for an insider purchase, an opportunistic insider purchase, an opportunistic insider sale, a routine insider purchase, or a routine insider sale. The dummies equal one if the stock in week t has such an insider trade. To check the lead-lag relation where retail investors may follow insider trades, we employ another setting as follows, where the dependent variable is stock i's retail order imbalance in week *t+1* ($\mathrm{Oib_{i,t+1}}$):

$$Oib_{i,t+1} = a + b * Ins_{i,t} + c * X_{i,t-1} + \epsilon_{i,t} \tag{4}$$

The control variables $\mathrm{X_{i,t\text{-}1}}$ include firm size (LSIZE), book-to-market ratio (LBM), turnover (TURN), idiosyncratic volatility (IVOL), the past 6-month momentum (MOM), the prior month return (RET1), the prior week return (RET1W), investor general attention (ATT), as well as retail investor attention (ASVI). Specifically, LSIZE is the natural logarithm of market capitalization. LBM is the natural logarithm of the most recent fiscal year-end book value divided by the market capitalization. MOM is the past cumulative returns from the month -7 to the month -2. RET1 is the prior month's return. TURN is the monthly trading volume divided by the average number of shares outstanding over the past 12 months. IVOL is the standard deviation of the residuals from the Fama-French three-factor regressions of daily stock excess returns over the previous 6 months. ATT is the weekly average of the daily trading volume divided by the average trading volume in the previous year (252 trading days). ASVI is the weekly abnormal change in Google Search

Volume Index. We run weekly panel regressions for all stocks with insider trades during the week, with week fixed effect and two-way (firm and week) clustered standard errors.

The results are reported in Table 4. Consistent with Figure 1 and Table 2, retail investors trade on the same side with insiders when insiders purchase the stock. Furthermore, retail investors tend to follow informed insider purchases (opportunistic buys) rather than uninformed ones (routine buys). Models (1)-(2) show the results when the dependent variable is *oibvol*. The coefficient on the insider buy dummy (Buy) is 0.125 with a t-statistics of 10.45, and the coefficient on the opportunistic insider buy dummy (Opp_buy) is 0.104 with a t-statistics of 4.42. The coefficient on the routine buy dummy (Rou_Buy) is -0.002 and statistically insignificant.

[Table 4 here]

Results in Model (1) and Model (2) suggest that stocks with insider purchases have 12.5% higher retail *oibvol* in the current week compared to stocks with insider sales, and stocks with opportunistic insider purchases have 10.4% higher retail *oibvol* in the current week compared to stocks without opportunistic insider purchase. Model (3) and Model (4) show the results when the dependent variable is *oibtrd*. Stocks with insider purchases have 11.3% higher retail *oibtrd* in the current week compared to stocks with insider sales, and stocks with opportunistic insider purchases have 11.8% higher retail *oibtrd* in the current week compared to stocks without opportunistic insider purchase. Results in Models (5)-(8) for retail order imbalance in week t+1 remain consistent with the contemporaneous tests, although the coefficients on main independent variables decrease in magnitude.

As a robustness check, we also conduct daily-frequency test. In Table A3 we run daily regressions using the same specification as in Table 4. Consistent with the weekly tests, the results show that retail order flow is in the same direction with aggregate insiders trade at the event day. This also applies for opportunistic insider purchases.[20]

Overall, the regression results indicate that retail order imbalances are consistent with insider purchases in the event week, especially with informed insider purchases. This finding

[20] The significantly negative coefficient on the opportunistic insider sell dummy suggests that retail investors tend to sell the stocks with opportunistic insider sales.

is in contrast to previous findings that retail investors make systematic investment mistakes (e.g. Barber and Odean, 2000). More importantly, we show that retail investors as a whole do not blindly follow insider trades. Instead, their trading patterns around the insider trading window suggest that they tend to follow informed insider trades.

3.2 Retail Investor Attention

While our initial results appear consistent with retail investors following informed insider trades, other reasons may explain the observed pattern. It is plausible that insider trading increases retail attention at the aggregate level. A number of papers argue that investors' attention is limited when they are selecting stocks.[21] Barber and Odean (2008) show that retail investors are net buyers of attention-grabbing stocks, while it is not the case for selling because retail investors only sell what they own (short-sale is not common for retail investors). Da, Engelberg, and Gao (2011) further use Google search volume to proxy for the attention of retail investors, and show transitory price pressures on those attention-grabbing stocks.

We control for potential effect of investor attention by considering investor general attention (ATT, Barber and Odean, 2008) and retail investor attention (ASVI, Da, Engelberg, and Gao, 2011) in Table 4. Coefficients on both investor attention variables are positive and significant. However, after controlling for the general attention and retail investor attention, the coefficients of the main independent variables remain significant.

We also run the panel regressions separately for stocks with high and low investor attention. We use Abnormal Search Volume Index (ASVI) as the proxy for retail investor attention. We assign ASVI to be high when it is among the highest 33.3% of the sample, and low when it is among the lowest 33.3% of the sample. We then run regressions for the sub-samples $\mathrm{ASVI_t} = \mathrm{High}$ and $\mathrm{ASVI_t} = \mathrm{Low}$ separately, and report the coefficient estimates for Opp_Buy and Rou_Buy in Table 5, as well as coefficient differences between Model (1) and Model (3), and between Model (2) and Model (4).

[Table 5 here]

[21] See, Kahneman (1973) and Hirshleifer and Teoh (2003).

The key message from Table 5 is that the coefficients on Opp_Buy remain significantly positive for both high ASVI and low ASVI stocks, while the coefficients on Rou_Buy stay insignificant for both cases. Specifically, when the retail order imbalance is defined as *oibvol*, the coefficient on Opp_Buy is 7.8% (t-stat = 3.01) for the high attention sub-sample and 9.5% (t-stat = 3.58) for the low attention sub-sample. Similarly, when the retail order imbalance is defined as *oibtrd*, the coefficient on Opp_Buy is 10.3% (t-stat = 4.43) for the high attention sub-sample and 8.2% (t-stat = 3.44) for the low attention sub-sample. The coefficients on Rou_Buy become negative and insignificant when ASVI is low.

These results suggest that elevated investor attention is not a driving force for retail investors to follow insider trades. When there are insider purchases, retail investors tend to follow them, regardless of the level of the investor attention. For informed trades (opportunistic buys), retail investors follow them anyway; for uninformed trades (routine buys), increase in attention is affecting retail investor trading direction to some extent, although not statistically significant. These findings suggest that retail investors do not simply trade stocks due to higher attention.[22]

3.3 Common Sources of Information - Earnings Announcement

Another potential explanation of retail trading pattern is that retail investors and corporate insiders share the same set of information around the same time when making their trading decisions. Earnings announcement, which is critical to assess the fundamental value of a firm, is an important source of information for most investors including small retail investors. For example, Lee (1992) and Frazzini and Lamont (2021) find evidence of net small buys on the earnings announcement date and immediately after the event. Kaniel et al. (2012) observe that individuals are net sellers at the time of the earnings announcement and several days after the event, and net buyers before the event. Besides, they show that purchases (sales) of stocks by retail investors before the earnings announcements can predict returns after the announcements.

In our context, if retail investors and insiders share common (private) information about future earnings, it could explain why they trade in the same direction around the same time.

[22] We also use investor general attention (ATT) to separate the sample and find similar results.

To examine this possibility, we divide the sample of stocks into two sub-samples, those with near-future earnings news and those without. Specifically, we define the upcoming earnings announcement dummy $\mathrm{EA}_{[t+1,\ t+4]} = 1$ if there is an earnings announcement for the stock within 4 weeks after the insider trading event, and 0 otherwise. We then repeat the panel regressions for each sub-sample separately.

Panel A of Table 6 presents the regression results based on whether there is any earnings announcement in the upcoming month. Results show that retail investors follow opportunistic insider purchases regardless of any earnings announcement. When there is an upcoming earnings announcement, retail investors tend to follow opportunistic insider purchases. Specifically, the coefficient on Opp_Buy is 8.3% with the t-statistic of 2.02 when the retail order imbalance is defined as *oibtrd*, although for *oibvol* the corresponding coefficient is 2.4% with the t-statistic of 0.53. When there is no upcoming earnings announcement, the coefficient on Opp_Buy is 11.1% with the t-statistic of 7.68 when the retail order imbalance is defined as *oibtrd*, and for *oibvol* the corresponding coefficient is 11.3% with the t-statistic of 6.98. It is possible retail investors learn about earnings information ex-ante, and trade correspondingly. But for the majority of our cases when there is no earnings news, retail investors still follow insider trades. As comparison, retail investors do not follow routine insider purchases in either scenario.

[Table 6 here]

Furthermore, Kaniel et al. (2012) show that intense retail investors buying (selling) predicts large positive (negative) abnormal returns on and after earnings announcement. Thus, we further divide the sub-sample of $\mathrm{EA}_{[t+1,\ t+4]} = 1$ into cases when SUE >0 and SUE <0. SUE is defined as the three-day abnormal return around the earnings announcement event. Panel B reports the regression results based on whether there is a positive or negative SUE.

We do find that retail investors follow insider purchases more aggressively for stocks with positive future SUE than those with negative future SUE, which appears consistent with Kaniel et al. (2012). Specifically, when the retail order imbalance is measured as *oibtrd*, the coefficient on Opp_Buy is 0.187 (t-stat = 3.03) for SUE >0, and the corresponding coefficient is 0.048 (t-stat = 0.74) for SUE <0. The difference in the coefficient estimates in these two scenarios is however not statistically significant. The results are similar when the retail order imbalance is measured as *oibvol*. As for routine-purchased stocks, retail investors tend to purchase these stocks when positive SUE is expected, and they sell when negative SUE is expected. The difference between the two scenarios for the Rou_Buy is 30.0% (t-stat = 2.33) when the retail order imbalance is measured as *oibtrd*, and it is 49.9% (t-stat = 3.58) when the retail order imbalance is measured as *oibvol* . Regression results in Table A4 further verify our finding.[23]

Overall, results in this sub-section suggest that some retail investors might have information about future earnings. However, the upcoming earnings information is not a driving force for retail investors to follow informed insider trades, as they follow insider purchases for the vast majority of the cases when there is no near future earnings announcement.

3.4 Common Sources of Information - Analyst Revision

Another source of common information could be the near-future analyst forecast revision or recommendation change. Prior literature documents that (changes in) analyst recommendations yield abnormal future returns (e.g. Womack, 1996; Barber, Lehavy, Mcnichols, and Trueman, 2001; Jegadeesh, Kim, Krische, and Lee, 2004). Moreover, Malmendier and Shanthikumar (2007) and Mikhail, Walther, and Willis (2007) show that analyst recommendations are treated literally by retail investors.

To examine the effect of analyst recommendation changes/forecast revisions on retail trading patterns following insider purchasing, we repeat the above analysis, except that we use analyst recommendation changes and forecast revisions as the conditioning variables to divide the sample. We report the regression results for the sub-samples of recommendation upgrades and downgrades in the next month separately. We define the sub-sample as "Rec Upgrade" when the change in analyst recommendations within the next month after the insider trading week is positive. We define the sub-sample as "Rec Downgrade" when the change in analyst recommendations within the next month after the insider trading week

[23] Models (1)-(2) in Table A4 correspond to Table 6, Panel A, which investigates whether upcoming earnings news have any effect. Models (3)-(4) in Table A4 correspond to Table 6, Panel B, where the sample is narrowed to only include observations with upcoming earnings events.

is negative. The change in analyst recommendations is calculated as the next month consensus recommendation minus the consensus on the same stock in the past month. Table 6, Panel C reports the regression results conditioning on analyst recommendation change. Retail investors tend to follow informed (opportunistic) trades regardless of recommendation upgrades/downgrades, indicating that information about analyst revision do not drive the retail trading pattern following insider purchases. As for coefficients of routine buys, we find that retail investors do not follow routine purchases in both scenarios. Especially for *oibtrd*, the coefficient on Rou_Buy is -12.8% with a t-statistics of -1.89 when there is an upcoming downgrade.

We further report the regression results for the sub-samples of stocks with analyst earnings forecast up revision and down revision in the next month separately. We define Forecast Up Revision as when the change of analyst EPS forecast is positive. We define Forecast Down Revision as when the change of analyst EPS forecast is negative. The change of analyst EPS forecast is calculated as the next month EPS Median Estimate averaged across all analysts minus the same average forecast for the same stock in the past month. Results in Panel D also show that retail investors follow opportunistic insider purchases regardless if there is any analyst forecast revision. Specifically, coefficients on Opp_Buy remain significantly positive in both scenarios, for both measures of the retail order imbalance *oibvol* and *oibtrd*. Coefficients on Rou_Buy is insignificant in all cases. Overall, neither the analyst forecast revision nor the recommendation change provides an explanation for retail investors following opportunistic insider purchase. Retail investors follow insider trades not because they share the common information with insiders. It is likely that they follow insider trades because of the private information content revealed from these informed trades, which is not yet incorporated into prices.

4 Price Discovery of Retail Trades around Insider Trades

As shown in the previous section, the trading pattern of retail investors, i.e. following informed insider trades during the event window, is likely due to their observing information from insider trades. Prior literature document that traders who possess private information help promote price efficiency, by moving stock prices closer to their fundamental values (e.g. Kyle, 1985; Diamond and Verrecchia, 1987). If retail investors learn about private information revealed by insider trading, they should help expedite the price discovery process of the underlying stocks by trading alongside insiders.

In this section, we employ portfolio analysis and panel regressions of future returns to test the above hypothesis. We then decompose the retail trades into three components to further examine whether results in the previous sections are driven by information, liquidity provision, or price pressure. We also examine the effect of information asymmetry on the return premiums by retail trading following insider purchases. Lastly, we provide evidence on the price efficiency gain using variance ratio and price delay measure.

4.1 Portfolio Returns

If retail investors expedite price discovery by following opportunistic insider purchases, we would expect high future returns for stocks they purchase. We construct event-week portfolios based on whether retail investor purchase or sell the stocks that opportunistic insider have bought during the event week. The portfolio "Follow" include stocks with positive *oibvol* during the event week, and "Not-Follow" include those with negative *oibvol* during the event week. We use CRSP daily value-weighted market returns to calculate the average weekly market return, and subtract it from weekly stock return to get the weekly market-adjusted return for each portfolio. Table 7 reports next-week returns as well as cumulative returns for the next 4 weeks, 12 weeks, 18 weeks, 24 weeks and 52 weeks, respectively.

[Table 7 here]

For stocks with opportunistic insider purchases, those that retail investors have bought yield 10 bps higher returns the next week than those that retail investors have sold. The weekly cumulative return difference between the two groups remains significantly positive until week 18, peaking in week 12 at 22 bps before gradually decreasing. There is no future return reversal, inconsistent with temporary price pressure from the retail trading or retail investors providing liquidity. Results here indicate that some retail investors, by observing insider information and trading alongside them, help expedite price discovery to its fundamental value for insider-purchased stocks.

[Figure 2, Figure 3 here]

Figure 2 plots the cumulative abnormal returns (market-adjusted and size-BM-adjusted) of the Follow and Not-Follow portfolios. Both Panel A and B show that the cumulative abnormal return difference between the Follow and Not-Follow portfolios increases in the first 12 weeks and then decreases over time, indicating a converging trend between the two groups. Panel C and D show that for stocks with routine insider purchases, the corresponding cumulative return difference is negative over time, which is consistent with routine-purchased stocks containing no valuable information (Cohen, Malloy, and Pomorski, 2012).

For stocks with opportunistic and routine purchases, we further construct a long-short portfolio (Follow – Not-Follow) and plot its cumulative abnormal returns in Figure 3. Consistent with results from Table 7, for stocks with opportunistic insider purchases, the long-short portfolio earns statistically significant positive abnormal returns up to 4 months. For comparison, the long-short portfolio earns insignificant cumulative returns over time for stocks with routine insider purchases.[24]

We conduct calendar-week portfolio analysis as an additional test. Each week for the stocks with opportunistic insider purchases, we construct the Follow – Not-Follow portfolio as defined before. We rebalance the portfolio either every week or every four weeks. For each portfolio, we calculate the equal-weighted weekly returns, the CAPM alphas, the Fama and French (1993) three-factor alphas, and the Carhart (1997) four-factor alphas.

[Table 8 here]

Table 8 reports the weekly alphas for the retail Follow portfolio and Not-Follow portfolio, as well as those for the long-short portfolio (Follow - Not-Follow). Specifically, the equal-

[24] We also check for 1-year horizon, and find that for stocks with opportunistic insider purchases, the long-short portfolio earns positive cumulative return without return reversal. For stocks with routine insider purchases, the long-short portfolio's cumulative return starts to become negative from week 30.

weighted portfolio that goes long Follow portfolio and goes short Not-Follow portfolio earns a CAPM alpha of 7.3 bps (t-stat = 2.01) and a Carhart alpha of 7.9 bps (t-stat = 2.15) the next week. Both the CAPM alpha and Carhart alpha remain significant until week 4, when the CAPM alpha becomes 3.6 bps per week (t-stat = 1.70) and the Carhart alpha becomes 3.6 bps per week (t-stat = 1.68).

Collectively, evidence in this section suggests that by taking advantage of information revealed from informed insiders, retail investors help expedite the price discovery process for the underlying stocks. By purchasing these stocks, retail investors move the stock prices to their fundamental values faster than those who sell the stocks.

4.2 Panel Regressions

We next conduct panel regressions to explain the retail trades' information content around insider trades. We use two settings for the empirical design. We regress one-week-ahead stock return on the opportunistic insider purchase dummy (Opp_Buy), the routine insider purchase dummy (Rou_Buy), as defined in Table 4, and the retail investor purchase dummy (Retail_Buy). Retail_Buy equals 1 if retail investors buy the stock, and 0 if they sell the stock. We also include interaction terms Opp_Buy * Retail_Buy and Rou_Buy * Retail_Buy. We then run the following panel regression:

$$
\begin{aligned}
Ret_{i,t+1} = a + b * Opp\_Buy_{i,t} + c * Rou\_Buy_{i,t} + d * Retail\_Buy_{i,t} + e * Opp\_Buy_{i,t} \\
* Retail\_Buy_{i,t} + f * Rou\_Buy_{i,t} * Retail\_Buy_{i,t} + g * X_{i,t} + \epsilon_{i,t} \quad (5)
\end{aligned}
$$

We include firm size, book-to-market ratio, turnover, idiosyncratic volatility, momentum, short-term reversal, prior week return, investor attention as well as retail investor attention as control variables. The regression results are reported in Table 9.

[Table 9 here]

Model (1) in Table 9 shows the return predictability of opportunistic insider buys and routine insider buys. It provides out-of-sample evidence of Cohen, Malloy, and Pomorski

(2012) about the informational role of different insider types. Cohen, Malloy, and Pomorski (2012) conduct portfolio tests to examine next-month abnormal returns for stocks with opportunistic and routine insider trades. Similarly, our weekly panel regressions show that stocks bought by opportunistic insiders earn significantly higher returns the next week, while stocks bought by routine insiders do not earn significantly higher returns the next week. Specifically, a stock with opportunistic insider purchase (Opp_Buy) has 13 bps (t-stat = 7.25) higher return the next week compared to the remaining sample. On the other hand, Rou_Buy predicts a 3 bps higher next-week return with a t-statistics of 0.80.

Model (2) shows that stocks bought by retail investors earn significantly higher returns the next week than those sold by retail investors. The coefficient on the Retail_Buy dummy is 2 bps (t-stat = 6.47), consistent with Boehmer et al. (2021). The magnitude of Retail_Buy coefficient is only about 15.4% of the magnitude of Opp_Buy coefficient in Model (1). It is not surprising that retail trades are not as informative as informed insider trades. What are the sources of information for retail investors? They may be adept at incorporating insider-trading information, or have information that is unrelated to insider information. We test these alternatives and report results in Model (3) of Table 9.

We include the interaction terms Opp_Buy * Retail_Buy and Rou_Buy * Retail_Buy in Model (3). For stocks with opportunistic insider purchases, those that retail investors buy earn higher returns next week, with the coefficient on the interaction term Opp_Buy * Retail_Buy equals 7 bps (t-stat = 2.04). The statistically and economically significant coefficient on Opp_Buy * Retail_Buy suggests that retail investors learn from the opportunistic insider purchases, and they help impound the private information revealed from the informed insider trades into stock prices. By comparison, the coefficient on the interaction term Rou_Buy * Retail_Buy is not significant. As expected, retail investors do not earn significantly higher returns by following routine trades, which contain no valuable information.

In the second regression setting, we focus on the stocks with opportunistic insider purchases. Specifically, we run the following panel regressions of next-week returns on Follow_Oppbuy, controlling for other stock characteristics ($X_{i,t}$):

$$Ret_{i,t+1} = a + b * Follow\_Oppbuy_{i,t} + c * X_{i,t} + \epsilon_{i,t} \tag{6}$$

Follow_Oppbuy equals 1 if retail investors buy stocks in the event week following opportunistic insider purchases, i.e., positive *oibvol*, and equals 0 if they sell stocks in the event week following opportunistic insider purchases, i.e., negative *oibvol*.

The result is shown in Model (4) of Table 9. For stocks with opportunistic insider purchases, those that retail investors buy earn 7 bps higher return next-week. Again, the result is consistent with that retail investors observing insider information and trading along with insiders. Furthermore, we conduct daily-frequency tests with the same setting in Table A5 and Table A6. The results remain consistent. Overall, both portfolio analysis and panel regressions in this section indicate that retail investors learn from informed (opportunistic) insider purchases and their trading alongside insiders helps speed up price discovery.

4.3 Decomposing Retail Order Imbalance around Insider Trades

As we discussed in the previous section, there are alternative explanations for the return premium of stocks bought by retail investors following opportunistic insider purchases. One potential explanation is that retail investors possess information that is orthogonal to insiders' information. Our earlier results on retail trading controlling for earnings announcements, analysts forecast revision and recommendation updates in Section 3 are against this hypothesis. Moreover, portfolio tests in this section show that when retail investors sell stocks that opportunistic insider have purchased, these stocks still have higher future returns, albeit not as high as those that bought by retail investors. It seems that retail investors do not have superior information during the insider trading window on top of that possessed by insiders.

Prior literature documents that retail traders benefit from their liquidity provision (e.g. Kaniel, Saar, and Titman, 2008; Kaniel, Liu, Saar, and Titman, 2012). In our context, because retail investors trade in the same direction with insiders, they are not providing liquidity to insiders. However, it is possible that retail investors provide liquidity to other market participants who trade against them, and earn profits from the liquidity provision.

Apart from liquidity provision explanation, price pressure may also lead to the above return premium in the short-run. For example, Chordia and Subrahmanyam (2004) point out the persistence of order flow which results in the predictability of future stock returns. They denote this phenomenon as the "price pressure hypothesis". By decomposing the retail order imbalance into three components related to price pressure, liquidity provision and information, Boehmer et al. (2021) show that nearly half of the predictive power of the retail order imbalance comes from price pressure (order imbalance persistence), and most of the rest comes from the information component.

We follow Boehmer et al. (2021) and conduct a two-step decomposition of retail order imbalance into three components: Retail_Buy_Persistence, Retail_Buy_Contrarian and Retail_Buy_Other.[25] In the first step, we estimate the following regression model:

$$Retail\_Buy_{i,t} = a_t + b_t * Retail\_Buy_{i,t-1} + c_t * Ret_{i,t-1} + \epsilon_{i,t} \tag{7}$$

For each week t, we obtain the cross-sectional means of a, b and c as $\widehat{a_t}$, $\widehat{b_t}$ and $\widehat{c_t}$, respectively. We then compute Retail_Buy_Persistence as $\widehat{b_t}$ * $\text{Retail\_Buy}_{\text{i,t-1}}$. We compute Retail_Buy_Contrarian as $\widehat{c_t}$ * $\text{Ret}_{\text{i,t-1}}$. The residual part from the first-stage regression is denoted as Retail_Buy_Other, which is likely driven by informational content. In the second stage, we run panel regressions similar to Table 9, except that we replace Retail_Buy with the three components that we compute in the first stage. We include the same set of control variables as in Table 9. We include week fixed effects for all models. Standard errors are two-way clustered at the firm and the week level in all models.

Table 10 reports the second-stage regression results of the decomposition analysis. Model (1) shows that for general retail buys without opportunistic insider purchases, the abnormal returns from retail purchasing come from both the persistence (price pressure) component (Retail_Buy_Persistence predicts a 10 bps positive return next week with t-stat = 5.31) and the residual (information) component (Retail_Buy_Other predicts a 2 bps positive return next week with t-stat = 5.72), where the magnitude of price pressure component is 5 times as large as information component. However, for stocks with opportunistic insider purchases, the coefficients on the interaction terms of the three components with Opp_Buy indicate that the return predictability mostly come from the information component. The interaction term Opp_Buy * Retail_Buy_Other predicts a 7 bps positive return next week, with a t-statistic of 2.06. The magnitude (7 bps) is much larger than that of the general retail trading (2 bps),

[25] We also follow Kaniel et al. (2012) decomposition method and find information part mostly explains our above results. However, Boehmer et al. (2021) methodology suits our scenario better as it also involves retail order imbalance.

indicating that the information content is an essential driver for the return predictability of the retail trading following opportunistic insider purchases.

[Table 10 here]

For comparison, in Model (2) we also examine the predictive power for Rou_Buy, with all else equal, and find that neither of the three components explains the return premium. Our results remain consistent when we include both Opp_Buy and Rou_Buy and corresponding interaction terms in Model (3).

In Model (4), we restrict the sample to stocks with opportunistic insider purchases only, and interact Follow_Oppbuy dummy (whether retail investors buy or sell these stocks) with the three retail buy components as constructed above. The t-statistics for the interaction terms Follow_Oppbuy * Retail_Buy_Persistence and Follow_Oppbuy * Retail_Buy_Contrarian show insignificance. By comparison, the coefficient on the interaction term Follow_Oppbuy * Retail_Buy_Other predicts a 1.7% positive future return with a t-statistic of 2.55.

Overall, the two-step decomposition of the retail order imbalance on stocks with opportunistic insider purchases shows that the return predictability does not come from price pressure or liquidity provision. Instead, it most likely comes from the information that retail investors learn from insider trades.

4.4 Information Asymmetry and Stock Returns

Information asymmetry between informed and uninformed investors affect stock return. O'Hara (2003) and Easley and O'hara (2004) use information-risk models to demonstrate that returns are positively related to information asymmetry when investors rely more on private information. Coupled with limits to arbitrage theory, as price deviates from fundamental value,[26] informed investors could earn return premiums with long persistence. If retail investors indeed help impound private information into prices by trading along with informed insiders, we expect this effect to be stronger for stocks with higher ex-ante information asymmetry. In this sub-section, we sort stocks on their ex ante information asymmetry,

[26] See, for example, Long, Shleifer, Summers, and Waldmann (1990) and Shleifer and Vishny (1997).

and examine whether the return premiums become larger when the ex-ante information asymmetry is higher.

For stocks with opportunistic insider purchases, we first separate them into the Follow portfolio and the Not-Follow portfolio, based on whether retail investors follow insiders as defined in Table 1. We then categorize stocks into three levels of information asymmetry. For each level, we compute the difference in the cumulative market-adjusted returns between the Follow portfolio and the Not-Follow portfolio, up to 24 weeks. We use three proxies for the ex-ante information asymmetry. The first proxy is firm size, which is defined as the logarithm of the market capitalization.[27] Prior literature shows that small firms usually have higher information uncertainty as they are less diversified and have less information available than large firms. Additionally, we use idiosyncratic volatility to proxy for information asymmetry, as Pástor and Veronesi (2003) show a positive relation between information asymmetry and idiosyncratic return volatility. Lastly, we use Amihud (2002) illiquidity as the third proxy for information asymmetry.

[Table 11 here]

Table 11 reports the effect of retail investors following opportunistic insider purchases on market-adjusted returns for stocks with different levels of information asymmetry. Results show that the cumulative return differences are larger for stocks with smaller size, higher idiosyncratic volatility, or higher Amihud illiquidity. For instance, from the lowest idiosyncratic volatility tercile to the highest tercile, the 4-week cumulative abnormal return of the long-short (Follow – Not-Follow) portfolio increases by 61 bps.

The above findings further support our hypothesis that by trading alongside with informed insiders, retail investors help impound valuable information into the underlying stock prices, and such effects are stronger for stocks with higher ex-ante information asymmetry. In contrast to Gromb and Vayanos (2010) who document the irrational buying decisions of individual investors creating more mis-pricing, our paper indicates that individual investors are not necessarily irrational, but help improve price efficiency through informed trading.

[27] The use of firm size as a proxy is common. It is justified in papers such as Atiase (1985), Bamber (1987) and Llorente, Michaely, Saar, and Wang (2002).

4.5 Testing Price Efficiency Using Variance Ratio and Price Delay Measure

In this sub-section, we further examine the efficiency gain of retail trading via two commonly-used measures: the Lo and MacKinlay (1988) variance ratio and the Hou and Moskowitz (2005) price delay measure.

According to efficient pricing models, relative informational efficiency can be measured as how closely transaction prices resemble a random walk. Given information arrival and market frictions, price trajectory deviate from efficient prices temporarily. Testing the informational efficiency of prices can be done by examining how fast those deviations disappear over time.[28] Following Lo and MacKinlay (1988), we first use variance ratios (long-term to short-term return variances) to measure price efficiency. VR(n,m) represents variance ratio of the m-day return variance per unit time divided by the n-day return variance per unit time estimated, using daily returns next month. We compute |1- VR(n,m)| to examine the gap between the actual and the efficient prices in either direction. The null hypothesis is that |1- VR(n,m)| equals 0 in an efficient market: we expect that the retail trading negatively predicts |1- VR(n,m)| if they improve the price efficiency. We test the variance ratios in terms of (1, 10) and (1, 20) days. We repeat the previous panel regressions, except that we use variance ratios as the dependent variables. The results are presented in Table 12, Models (1)-(4).

[Table 12 here]

The first 4 Models in Table 12 show that the coefficient of interaction term Opp_Buy * Retail_Buy is significantly negative. In addition, Follow_Oppbuy significantly predicts a negative next-month |1- VR| for stocks with opportunistic insider purchases. The coefficient on Opp_Buy * Retail_Buy is -0.0145 (t-stat = -1.82) for |1- VR(1, 10)| and -0.0459 for |1- VR(1, 20)|. The coefficient on Follow_Oppbuy is -0.0169 (t-stat = -2.05) for |1- VR(1, 10)| and -0.0561 for |1- VR(1, 20)|. By comparison, the coefficient on Rou_Buy * Retail_Buy is statistical insignificant. The tests on the variance ratio suggest that following opportunistic insider purchases, retail investors improve informational efficiency on the stocks they buy.

[28] See, for example, Barnea (1974), Lo (2004) and Chordia, Roll, and Subrahmanyam (2005) documenting about random walk, adaptive market hypothesis and astute traders.

We next conduct panel regressions analysis of the price delay measure. The price delay measures the relative price efficiency by quantifying the speed of the adjustment to the market-wide information (Morck, Yeung, and Yu, 2000; Griffin, Kelly, and Nardari, 2010; Saffi and Sigurdsson, 2010; Boehmer and Wu, 2013). We adopt Hou and Moskowitz (2005)'s measure to estimate how quickly prices incorporate the information retail investors learn from insider trades. Note that the information applied in price delay measure is of market type whereas the variance ratio mostly measures firm-level information, and thus the two sources of information differ fundamentally. As our data is in daily frequency as opposed to Hou and Moskowitz (2005)'s monthly frequency, we compute the price delay measure by calculating the R^2 based on daily market return and stock return as follows:

$$r_{i,t} = a_i + b_i * R_{m,t} + \sum_{n=1}^{5} R_{m,t-n} + \epsilon_{i,t} \tag{8}$$

$\mathrm{R}_{\mathrm{m,t}}$ represents the daily market return and $\mathrm{r}_{\mathrm{i,t}}$ represents the daily stock return. We calculate price delay measure as 1 - [(R^2(restricted model) / R^2(unrestricted model))], where we compute R^2(restricted model) by restricting the coefficients on lagged market returns to be zero. A larger price delay indicates that the stock incorporates market-wide information with a slower speed.

Results for the price delay regressions are shown in Models (5)-(6) in Table 12. The corresponding coefficient on Opp_Buy * Retail_Buy in the full sample is negative but insignificant (coeff. = -0.4369 with t-stat = -0.35). The magnitude of the coefficient on Follow_Oppbuy is slightly larger (coeff. = -1.3602) but only marginally significant at the 10% level. These results show little gain in price efficiency measured by the price delay. As we mentioned earlier, the variance ratio mostly measures the firm-level information incorporated into prices, where the price delay measures the speed of the market information incorporated into prices. The empirical results in this sub-section indicate that the trading of retail investors alongside informed insiders helps impound firm specific information, rather than the aggregate market-wide information, into stock prices faster.

4.6 Retail and Institutional Trading Patterns in Longer Horizons

We further examine whether retail investors trade on the same direction with insiders in longer horizons. Prior studies show that insider purchases yield significant and persistent returns. Jeng, Metrick, and Zeckhauser (2003) find that insider purchases earn cumulative abnormal returns of more than 6% over the subsequent 100 trading days. Cohen, Malloy, and Pomorski (2012) document that the 12-month event-time return on the opportunistic long-short portfolio (opportunistic buys - opportunistic sells) is more than 5%, with no future reversal. We provide evidence in Section 4.1 that stocks purchased by opportunistic insiders earn positive and significant cumulative returns up to one year. A natural question is whether retail investors continue to trade in the same direction as insiders during the following months, and whether they can potentially benefit from the persistent positive returns.

We first examine the longer-term retail trading pattern. We employ the same econometric specification and the set of control variables as in Section 3.1, except that we replace the dependent variable with retail order imbalances in each of the subsequent four quarters.[29]

[Table 13 here]

The results are reported in Panel A of Table 13. During the quarter with the insider trading event, retail investors trade in the same direction as insiders in general (model 1), and the same as opportunistic insiders (model 2) if they make purchases. Models (1)-(2) show positive and significant coefficients on Buy and Opp_buy, respectively. Further, retail investors during the following year keep buying the stocks that insiders have bought. The coefficients on Buy (models 3, 5, 7, and 9) remain statistically significant, although much smaller in magnitude, in the following four quarters. Meanwhile, for stocks with opportunistic insider purchases, retail investors generally buy them in the subsequent year, but the coefficients on Opp_buy (models 4, 6, 8, and 10) are no longer statistically significant.

Next, we examine institutional trading subsequent to insider purchases. We regress the change in institutional ownership of a stock on insider trading dummy variables (main vari-

[29] We also check retail order imbalance in each of the subsequent twelve months, and the result remains similar. We do not report it here for brevity.

ables of interest: Buy and Opp_Buy) for that stock. We measure the change in institutional ownership in each of the four quarters following insider purchases. Panel B of Table 13 indicates that for stocks bought by insiders in general (model 1) and opportunistic insiders (model 2), institutional investors trade on the opposite direction with these insiders in the contemporaneous quarter. The coefficient on Buy is -0.5% (t-stat = -3.28) and the coefficient on Opp_Buy is -0.5% as well (t-stat = -2.76). We further find that institutional investors keep (short) selling the stocks that insiders have bought in the subsequent year. According to models 3, 5, 7, and 9, the Buy coefficients are all negative, but their magnitudes decrease over time and become statistical insignificant after two quarters. After opportunistic insider purchases, institutional investors sell them for up to subsequent three quarters. The magnitudes are larger for the following two quarters (models 4 and 6) compared to those in the general insider purchasing case (models 3 and 5). After the subsequent two quarters, the coefficients on Opp_buy (models 8 and 10) are no longer statistically significant.[30]

Taken together, this sub-section provides empirical evidence that retail investors keep following (opportunistic) insider purchases over a longer horizon. On the other hand, besides contemporaneously providing liquidity to inside buyers, institutions continue to trade on the opposite side of (opportunistic) insiders in the subsequent year.

5 Additional Robustness Checks

5.1 Granger-type Causality Test

The reverse causality concern is that insiders may learn from the retail order imbalance. We run Granger-type causality test to address the direction of causality. We first regress the retail order imbalance of stock i in week t on the 1-week-lagged insider trading dummies. We then regress the insider trading dummies of stock i in week t on the 1-week-lagged retail order imbalance, both during the insider-trading event window. We run Fama-MacBeth regressions with Newey-West 5 lags adjusted and include similar control variables as in

[30] Cohen, Malloy, and Pomorski (2012) find that institutional investors buy those insider-purchased stocks in the following quarter. They aggregate the insider trading at the quarterly level. Our regressions are at the weekly level, and our sample period is after their sample ends.

Table 4. The results of Models (1)-(3) in Table A7 are consistent with those in Table 4, where more insider purchases are associated with higher next-week retail order imbalance *oibvol*.[31] Specifically, the dummy l_buy predicts a 7.3% increase in the retail order flow next week, with a t-statistic of 3.60. The dummy l_opp_buy predicts a 14.8% increase in the retail order flow next week (t-stat = 3.01) whereas the dummy l_rou_buy has a negative and insignificant coefficient. Results from Models (1)-(3) further corroborate the idea that retail investors follow insider trades. In particular, they follow informed insider trades (l_opp_buy) instead of the uninformed ones (l_rou_buy). Moreover, large and significant coefficients on the lagged order flow indicate that the retail order flow has high autocorrelation, consistent with Boehmer et al. (2021).

In Table A7 Models (4)-(6), we regress the insider trading dummy (Buy in (4), Opp_Buy in (5) and Rou_Buy in (6)) on the 1-week-lagged order imbalance (l_oibvol) to examine the reverse causality. Coefficients on l_oibvol are negative in all models, indicating that the buying decision of insiders is not significantly affected by past retail order imbalance. We also find high autocorrelation of opportunistic purchases and routine purchases, as adjacent insider trades are common in our sample. Overall, results in this sub-section suggest that retail investors follow informed insider purchases, not the other way round.

5.2 Sub-sample Tests

We conduct sub-sample tests to evaluate the robustness of our results. Specifically, we examine the effect of retail investors following opportunistic insider purchases on stocks with different characteristics. We include book-to-market ratio, prior month return, Google ASVI, institutional ownership as well as earnings surprise SUE as conditioning variables to divide the sample of stocks into three levels.[32] We further separate the sub-sample stocks into the Follow portfolio and the Not-Follow portfolio, based on whether retail investors follow insiders as defined in Table 1. We then compute the difference in the cumulative market-adjusted returns between the Follow portfolio and the Not-Follow portfolio, up to 24 weeks,

[31] We also use *oibtrd* as (in)dependent variable and find similar results. We do not report it for brevity.

[32] Prior literature documents that these stock characteristics may affect stock returns significantly. See, for example, Fama and French (1995), Da, Engelberg, and Gao (2011), Edelen, Ince, and Kadlec (2016), Kaniel et al. (2012), and Doyle, Lundholmn, and Soliman (2006).

in each sub-sample. The results are presented in Table A8. We find that the return premium of Follow − Not-Follow is not concentrated in stocks with certain types.

6 Conclusion

Using the comprehensive TAQ data and following the approach in Boehmer et al. (2021), we identify daily retail trading, and document evidence consistent with informed trading of retail investors. Retail investors buy more aggressively right after the insiders' opportunistic purchases, but not after the insiders' routine purchases. There is an increase in the abnormal retail downloads of the Form 4 filings from the EDGAR databases for the opportunistic insider purchases. The retail purchases are also higher with higher abnormal Form 4 downloads by retail investors. These trading patterns cannot be explained by the increased attention on these stocks, or by the shared common information between retail investors and corporate insiders, such as information on upcoming earnings announcements, analyst forecast revisions, or updates on analysts recommendation. Retail investors keep following (opportunistic) insider purchases in subsequent four quarters as well.

Moreover, for stocks with opportunistic insider purchases, those bought by retail investors experience significantly higher returns than those sold by retail investors, up to 18 weeks. In panel regressions of stock returns on an opportunistic insider purchase dummy, a retail purchase dummy, and the interaction of the two, the coefficient on the interaction term is positive and statistically significant. A long/short portfolio strategy that longs the retail-buy stocks and shorts the retail-sell stocks for stocks with opportunistic insider purchases generates significant alphas. We further decompose retail trading into three components: price pressure, liquidity provision, and information. Only the information component significantly predicts future stock returns, and this effect is stronger for stocks with greater information uncertainty. Collectively, these results suggest that retail trading helps improve price efficiency by impounding information revealed from insider trading into stock prices. Further analysis suggests that retail trading following opportunistic insider purchases lowers future variance ratio, but not the price delay measure. To the extent that variance ratio measures the level of information efficiency at the firm level and that price delay measures at the market level, our results suggest that price discovery and efficiency gain through retail trading are mostly about the firm level information, rather than the market level information.

There is an ongoing debate with mixed evidence on the role of retail investors in financial markets, particularly regarding their informational role. Using the interaction with insider trading, we examine one specific source of information for retail investors. We show that at least some retail investors learn about private information revealed by insiders' opportunistic purchases. As retail investors face fewer restrictions relative to institutional investors and have fewer concerns over risk exposure, they can act promptly upon this information. Their trading predicts future returns and helps expedite price discovery.

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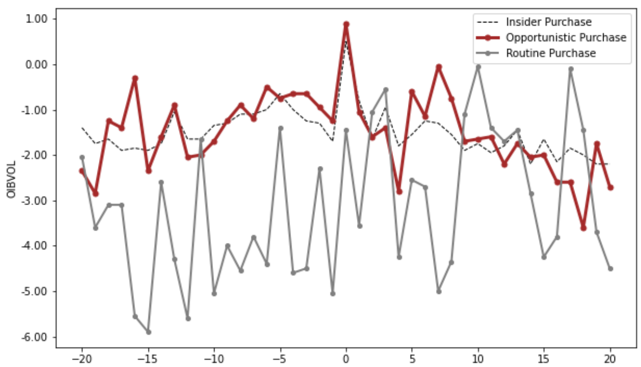
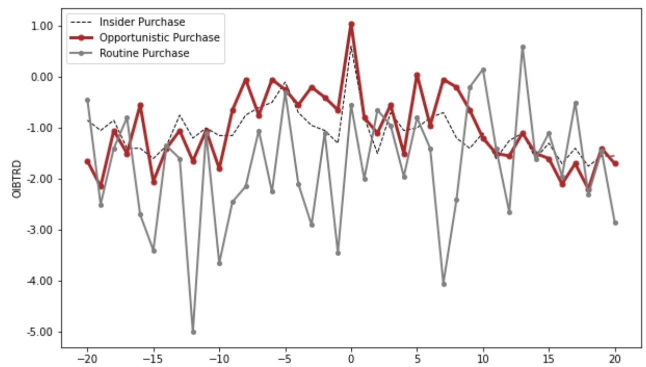
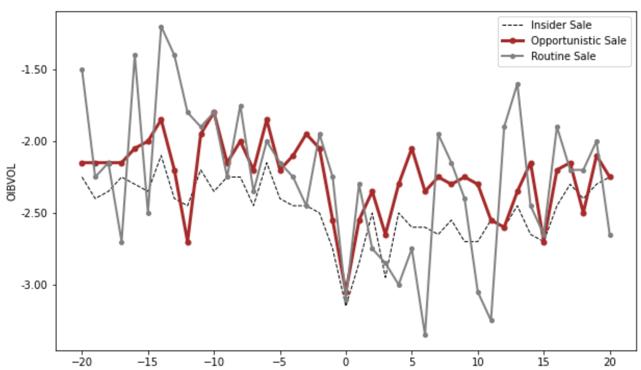


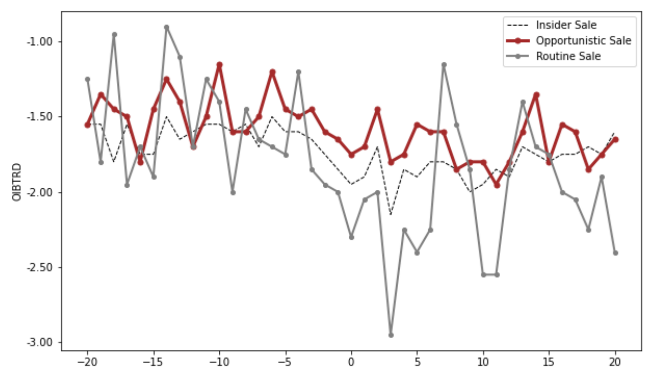
Panel A: *oibvol* around Insider Purchase Universe



Panel B: *oibtrd* around Insider Purchase Universe



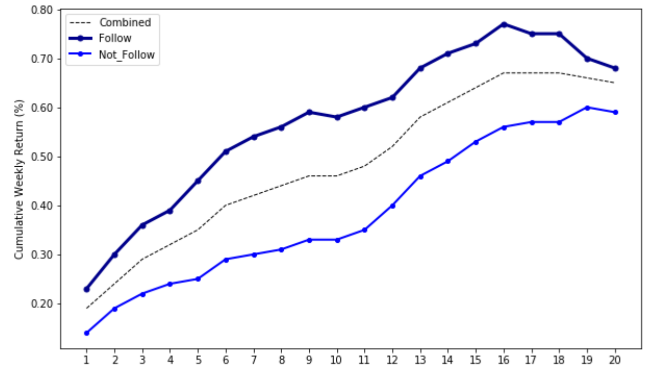
Panel C: *oibvol* around Insider Sale Universe



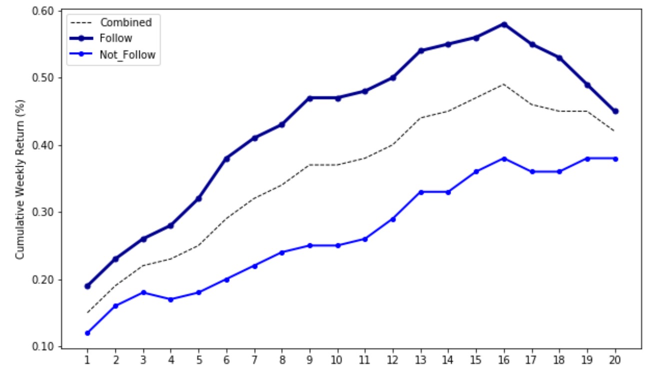
Panel D: *oibtrd* around Insider Sale Universe

Figure 1: Daily Retail Order Imbalance around Insider-Trading Event Windows

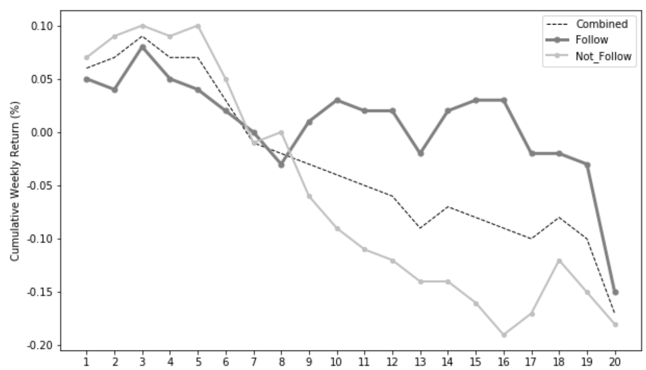
This figure presents the retail order imbalance, both *oibvol* and *oibtrd* around the insider trading window. Panel A reports *oibvol* in insider purchase universe. Panel B reports *oibtrd* in insider purchase universe. Correspondingly, Panel C and Panel D report order imbalance in insider sale universe. Each node is Newey-West adjusted and we use clustering method to make adjacent insider trades (within 5 days) as one trade.



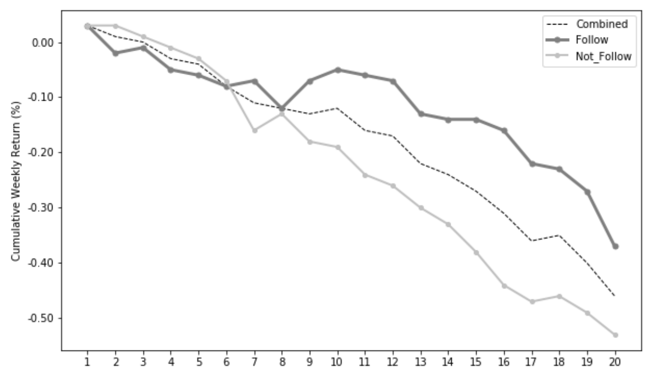
Panel A: Cumulative Mkt-adj Returns: Opportunistic Purchase



Panel B: Cumulative Size-BM-adj Returns: Opportunistic Purchase



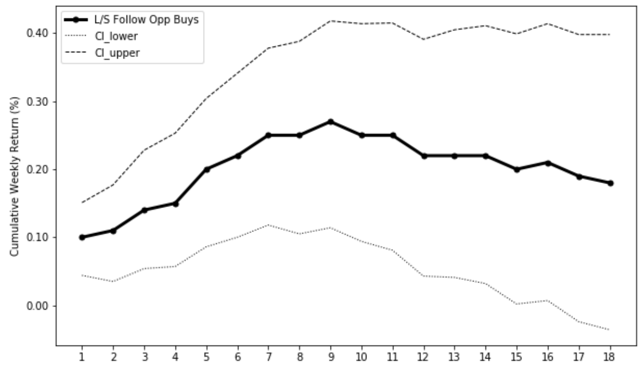
Panel C: Cumulative Mkt-adj Returns: Routine Purchase



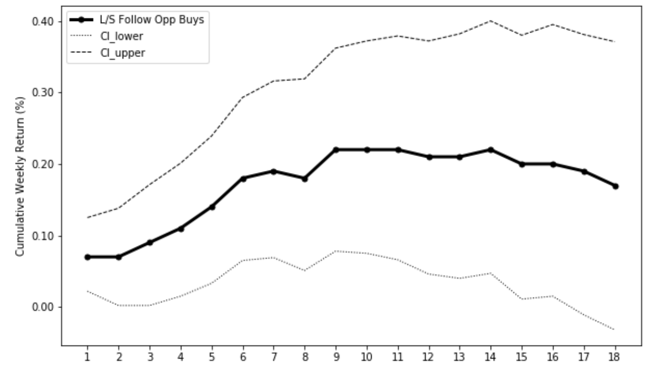
Panel D: Cumulative Size-BM-adj Returns: Routine Purchase

Figure 2: Cumulative Returns of Retail Investor Portfolios

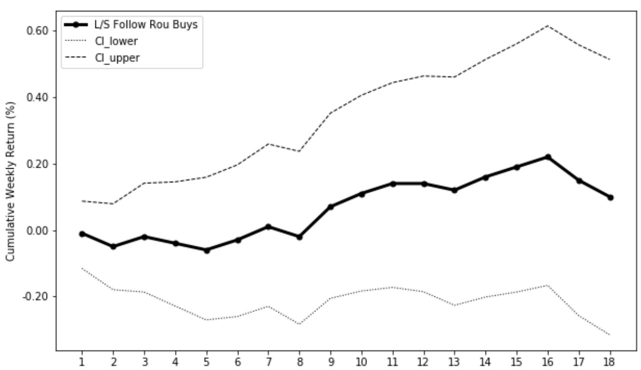
This figure presents the cumulative adjusted returns for stocks with opportunistic insider and routine insider purchases, up to 20 weeks, based on whether retail investors trade on the same side (Follow or Not-Follow) with opportunistic or routine insiders. Specifically, we divide the opportunistic/routine sample into two sub-samples based on whether retail investor purchase or sell the stock in the event week (from the insider purchase date to one day after the SEC filing date). We define Follow group to be the stocks with positive retail order imbalance *oibvol* during the event week, and Not-Follow group to be the stocks with negative retail order imbalance *oibvol* during the event week. Note that label named 'Combined' refers to the overall cumulative returns for the sub-sample, i.e. regardless of the sign of the retail order flow. We use CRSP daily value-weighted market returns to calculate the average weekly market return, and subtract it from weekly stock return to get the weekly market-adjusted return. We also construct 5*5 weekly size-BM benchmark portfolio return to get size-BM-adjusted return. Panel A reports the cumulative market-adjusted returns for stocks with opportunistic insider purchases, and Panel B reports the cumulative size-BM-adjusted returns for stocks with opportunistic insider purchases. Panel C and Panel D present the cumulative returns for stocks with routine insider purchases.



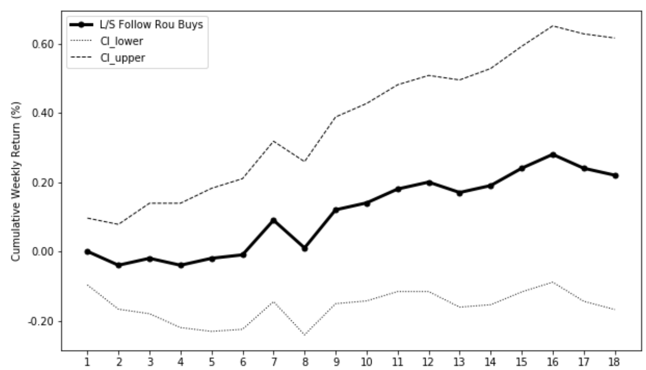
Panel A: Cumulative Mkt-adj Returns: Opportunistic Purchase



Panel B: Cumulative Size-BM-adj Returns: Opportunistic Purchase



Panel C: Cumulative Mkt-adj Returns: Routine Purchase



Panel D: Cumulative Size-BM-adj Returns: Routine Purchase

Figure 3: Long-Short Portfolio Returns in Insider Purchase Universe

This figure presents long-short portfolios of cumulative adjusted returns for stocks with opportunistic and routine insider purchases, up to 18 weeks, between retail investor investment choice (Long Follow portfolio and Short Not-Follow portfolio). Specifically, we divide the opportunistic/routine sample into two subsamples based on whether retail investor purchase or sell the stock in the event week (from the insider purchase date to one day after the SEC filing date). We define Follow group to be the stocks with positive retail order imbalance *oibvol* during the event week, and Not-Follow group to be the stocks with negative retail order imbalance *oibvol* during the event week. 95% confidence interval is shown in this figure, including upper and lower limit. We use CRSP daily value-weighted market returns to calculate the average weekly market return, and subtract it from weekly stock return to get the weekly market-adjusted return. We also construct 5*5 weekly size-BM benchmark portfolio return to get size-BM-adjusted return. Panel A reports the cumulative market-adjusted returns for stocks with opportunistic insider purchases, and Panel B reports the cumulative size-BM-adjusted returns for stocks with opportunistic insider purchases. Panel C and Panel D present the cumulative returns for stocks with routine insider purchases.

Table 1: Summary Statistics

This table reports summary statistics for retail order imbalance, insider trades, and firm characteristics over the sample period from Jan 2010 to Dec 2018. Panel A presents summary statistics for stocks that are traded by insiders or retail investors. All variables are calculated in weekly frequency. The retail order imbalance variable (*oibvol*) is computed as the difference between the number of shares bought and sold by retail investors, divided by the total number of shares traded by retail investors. Another order imbalance variable (*oibtrd*) is computed as the difference between the number of buy trades and sell trades by retail investors, divided by the total number of trades by retail investors. The number of shares purchased by insiders and the number of shares sold by insiders are presented in thousands. Panel B and Panel C present characteristics of stocks purchased and sold by insiders, respectively. The sample is further separated into sub-samples of stocks with insider purchase, insider opportunistic purchase, insider routine purchase, insider sale, insider opportunistic sale, and insider routine sale. In each sub-sample, we further divide the stocks based on whether retail investors trade on the same side (Follow) or the opposite side (Not-Follow) with insiders. Specifically, we follow Cohen, Malloy, and Pomorski (2012) and define a routine trader as the insider who has placed a trade in the same calendar month for at least three years in the past, and an opportunistic trader as the insider who has traded for at least three years in the past, but does not have an obvious discernible pattern. Panel B and C present characteristics of stocks traded by these various sub-groups. Firm size (LSIZE) is the natural logarithm of market capitalization. Book-to-market ratio (LBM) is the natural logarithm of the most recent fiscal year-end book value divided by the market capitalization. Momentums (MOM) is the past cumulative returns from month-7 to month-2, in percent. Short-term reversal (RET1) is the prior month's return, in percent. Turnover (TURN) is the monthly trading volume divided by number of shares outstanding, averaged over the past 12 months, in percent. Idiosyncratic volatility (IVOL) is the standard deviation of the residuals from the Fama and French (1993) three-factor regressions of daily stock excess returns over the previous 6 months, in percent. Investor attention (ATT) is the daily trading volume divided by the average trading volume in the previous year (252 trading days), and then take the weekly average (Barber and Odean, 2008).

Panel A: Summary Statistics for Insider Trades and Retail Trades

Variable	Mean	Std. Dev.	P25	Median	P75
oibvol	-0.021	0.275	-0.156	-0.013	0.114
oibtrd	-0.016	0.232	-0.133	-0.004	0.103
Number of shares purchased by insiders	233	7,220	2	10	42
Number of shares sold by insiders	228	3,379	6	20	63
Number of insider purchase trades	4.6	13.8	1	2	4
Number of insider sale trades	5.1	12.8	1	2	5

Table 1 (Cont.): Summary Statistics

Panel B: Characters of Stocks (Mean Value) Purchased by Insiders

	Insider Purchase		Routine Insider Purchase		Opportunistic Insider Purchase	
	Follow	Not-Follow	Follow	Not-Follow	Follow	Not-Follow
LSIZE	12.75	12.76	13.09	13.22	13.06	13.16
LBM	-0.56	-0.54	-0.47	-0.39	-0.52	-0.50
MOM	3.21	3.30	6.12	6.90	5.87	5.42
RET1	-1.41	-0.82	0.64	1.02	-1.09	-0.53
TURN	15.60	15.54	11.18	10.90	16.36	16.3
IVOL	1.31	2.59	1.76	1.74	2.31	2.18
ATT	1.53	1.44	1.14	1.27	1.52	1.52

Panel C: Characters of Stocks (Mean Value) Sold by Insiders

	Insider Sale		Routine Insider Sale		Opportunistic Insider Sale	
	Follow	Not-Follow	Follow	Not-Follow	Follow	Not-Follow
LSIZE	14.47	14.45	15.16	15.10	15.02	15.06
LBM	-1.14	-1.18	-1.37	-1.39	-1.16	-1.21
MOM	14.52	15.29	8.45	9.79	11.43	12.25
RET1	3.32	3.32	1.65	1.36	2.62	2.64
TURN	20.85	21.88	22.92	22.26	20.41	20.94
IVOL	1.90	1.97	1.68	1.70	1.60	1.63
ATT	1.17	1.25	1.03	1.09	1.10	1.14

Table 2: Retail Order Imbalance around Insider Trading Window

This table presents retail investor order imbalance around the event window over the sample period from Jan 2010 to Dec 2018. We define the event window as the days from insider trading date to one day after the SEC filing date of this trade. We report retail order imbalance 5 trading days around the event window. The retail order imbalance variable (*oibvol*) is computed as the difference between the number of shares bought and sold by retail investors, divided by the total number of shares traded by retail investors. Another order imbalance variable (*oibtrd*) is computed as the difference between the number of buy trades and sell trades by retail investors, divided by the total number of trades by retail investors. The sample is further separated into sub-samples of stocks with insider purchase, insider opportunistic purchase, insider routine purchase, insider sale, insider opportunistic sale, and insider routine sale. Specifically, we follow Cohen, Malloy, and Pomorski (2012) and define a routine trader as the insider who has placed a trade in the same calendar month for at least three years in the past, and an opportunistic trader as the insider who has traded for at least three years in the past, but does not have an obvious discernible pattern. Panel A presents the results for insider purchase universe and Panel B presents those for insider sale universe. To rule out the effect from nearby insider trades in our event window, we cluster the adjacent insider trades (within 5 days) for each stock into one group. We report the estimated mean with t-statistics (in parentheses). The standard errors are Newey-West adjusted. The mean values reported in this table are in percent.

Panel A: Retail Order Imbalance around Insider Purchase Event Window

Retail Order Imbalance	-5	-4	-3	-2	-1	Event Window	1	2	3	4	5
					All Insider Purchase Event Window						
oibvol	-0.7	-1.0	-1.3	-1.3	-1.7	0.5	-0.8	-1.7	-1.0	-1.8	-1.6
t-stat	(-1.98)	(-3.07)	(-3.75)	(-3.86)	(-5.90)	(2.59)	(-2.43)	(-4.92)	(-2.73)	(-5.28)	(-5.34)
oibtrd	-0.1	-0.7	-1.0	-1.1	-1.3	0.6	-0.8	-1.5	-0.7	-1.1	-1.0
t-stat	(-0.37)	(-2.49)	(-3.41)	(-3.63)	(-5.39)	(3.76)	(-2.86)	(-5.21)	(-2.40)	(-3.62)	(-4.03)
					Insider Purchase Opportunistic Event Window						
oibvol	-0.8	-0.7	-0.7	-1.0	-1.3	0.9	-1.1	-1.6	-1.4	-2.8	-0.6
t-stat	(-1.10)	(-0.95)	(-0.95)	(-1.38)	(-2.06)	(2.28)	(-1.58)	(-2.29)	(-1.99)	(-4.04)	(-0.94)
oibtrd	-0.3	-0.6	-0.2	-0.4	-0.7	1.1	-0.8	-1.1	-0.6	-1.5	0.1
t-stat	(-0.42)	(-0.95)	(-0.35)	(-0.70)	(-1.28)	(3.25)	(-1.42)	(-1.85)	(-0.94)	(-2.53)	(0.13)
					Insider Purchase Routine Event Window						
oibvol	-1.4	-4.6	-4.5	-2.3	-5.1	-1.5	-3.6	-1.1	-0.6	-4.3	-2.6
t-stat	(-0.86)	(-2.88)	(-2.72)	(-1.38)	(-3.57)	(-1.57)	(-2.24)	(-0.64)	(-0.29)	(-2.58)	(-1.82)
oibtrd	-0.3	-2.1	-2.9	-1.1	-3.5	-0.6	-2.0	-0.7	-1.0	-2.0	-0.8
t-stat	(-0.22)	(-1.63)	(-2.13)	(-0.81)	(-2.94)	(-0.70)	(-1.54)	(-0.47)	(-0.62)	(-1.39)	(-0.70)

Table 2 (Cont.): Retail Order Imbalance around Insider Trading Window

Panel B: Retail Order Imbalance around Insider Sale Event Window

Retail Order Imbalance	-5	-4	-3	-2	-1	Event Window	1	2	3	4	5
All Insider Sale Event Window											
oibvol	-2.4	-2.5	-2.5	-2.5	-2.8	-3.2	-2.9	-2.5	-3.0	-2.5	-2.6
t-stat	(-19.86)	(-20.01)	(-19.08)	(-18.92)	(-24.21)	(-47.82)	(-22.41)	(-18.74)	(-22.49)	(-20.07)	(-24.45)
oibtrd	-1.6	-1.6	-1.7	-1.8	-1.9	-2.0	-1.9	-1.7	-2.2	-1.9	-1.9
t-stat	(-15.61)	(-15.46)	(-15.57)	(-15.74)	(-19.54)	(-34.79)	(-17.98)	(-15.51)	(-19.65)	(-17.68)	(-21.25)
Insider Sale Opportunistic Event Window											
oibvol	-2.2	-2.1	-2.0	-2.1	-2.6	-3.1	-2.6	-2.4	-2.7	-2.3	-2.1
t-stat	(-11.04)	(-10.17)	(-9.03)	(-9.34)	(-13.53)	(-28.25)	(-11.82)	(-10.53)	(-12.13)	(-10.97)	(-11.37)
oibtrd	-1.5	-1.5	-1.5	-1.6	-1.7	-1.8	-1.7	-1.5	-1.8	-1.8	-1.6
t-stat	(-8.53)	(-8.72)	(-8.30)	(-8.53)	(-10.54)	(-19.15)	(-9.71)	(-7.89)	(-9.92)	(-10.16)	(-10.26)
Insider Sale Routine Event Window											
oibvol	-2.2	-2.3	-2.5	-2.0	-2.3	-3.1	-2.3	-2.8	-2.9	-3.0	-2.8
t-stat	(-4.10)	(-4.10)	(-4.20)	(-3.18)	(-4.23)	(-10.74)	(-3.95)	(-4.48)	(-4.79)	(-5.64)	(-5.75)
oibtrd	-1.8	-1.2	-1.9	-2.0	-2.0	-2.3	-2.1	-2.0	-3.0	-2.3	-2.4
t-stat	(-4.13)	(-2.61)	(-3.73)	(-3.88)	(-4.62)	(-9.11)	(-4.21)	(-4.00)	(-6.09)	(-5.01)	(-6.02)

Table 3: Retail Abnormal EDGAR Search and Corresponding Trades around Insider Trading Window

This table presents retail investors' abnormal EDGAR search as well as their order imbalance corresponding to high or low EDGAR search scenarios, all around the event window and over the sample period from Jan 2010 to Jun 2017. We define the event window as the days from insider trading date to one day after the SEC filing date of this trade. We report retail abnormal EDGAR search 5 trading days around the event window, and retail order imbalance 5 trading days after the event window. Panel A presents the retail investors' abnormal EDGAR search around insider trading event window. For each stock on each day, we count the number of unique IP addresses searching for Form 4 filings and then subtract its prior sixty-day average value to obtain *A_Search*. Panel B presents retail order imbalance at the event window and in the following 5 days, corresponding to high or low retail EDGAR search scenarios. During the event window, stocks in our sample are ranked into quintiles based on retail *A_Search*. We assign stocks within the top *A_Search* quintile into *High A_Search* group, and those within the bottom *A_Search* quintile into *Low A_Search* group. The retail order imbalance variable (*oibvol*) is computed as the difference between the number of shares bought and sold by retail investors, divided by the total number of shares traded by retail investors. Another order imbalance variable (*oibtrd*) is computed as the difference between the number of buy trades and sell trades by retail investors, divided by the total number of trades by retail investors. The sample is further separated into sub-samples of stocks with insider purchase, insider opportunistic purchase, insider routine purchase, insider sale, insider opportunistic sale, and insider routine sale. To rule out the effect from nearby insider trades in our event window, we cluster the adjacent insider trades (within 5 days) for each stock into one group. We report the estimated mean with t-statistics (in parentheses). The standard errors are Newey-West adjusted. The mean values reported in this table are in percent.

Panel A: Retail Abnormal EDGAR Search around Insider Trading Event Window

A_Search	-5	-4	-3	-2	-1	Event Window	1	2	3	4	5
All Insider Purchase Window	-2.04	-2.08	-2.12	-2.16	-2.11	2.36	-1.35	-1.51	-1.72	-1.81	-1.73
Insider Purchase Opportunistic Window	-2.02	-2.10	-2.16	-2.17	-2.16	2.59	-1.41	-1.55	-1.74	-1.86	-1.72
Insider Purchase Routine Window	-4.58	-4.72	-4.68	-4.78	-4.72	-0.81	-4.22	-4.45	-4.50	-4.51	-4.28
All Insider Sale Window	-2.09	-2.18	-2.31	-2.39	-2.37	0.80	-1.82	-1.99	-2.15	-2.16	-2.01
Insider Sale Opportunistic Window	-2.14	-2.28	-2.38	-2.43	-2.40	0.80	-1.78	-1.98	-2.15	-2.15	-2.04
Insider Sale Routine Window	-1.84	-2.07	-2.12	-2.35	-2.38	1.03	-1.76	-1.92	-2.05	-2.12	-1.88

Table 3 (Cont.): Retail Abnormal EDGAR Search and Corresponding Trades around Insider Trading Window

Panel B: Retail Order Imbalance in Different EDGAR Search Scenarios

Retail OIB		Event Window	1	2	3	4	5
		All Insider Purchase Event Window					
oibvol	High A_Search	2.50	1.55	-1.30	-0.25	-0.65	0.10
		(6.77)	(2.44)	(-1.91)	(-0.34)	(-0.90)	(0.13)
	Low A_Search	-1.35	-2.60	-2.90	-1.05	-1.20	-2.35
		(-3.08)	(-3.44)	(-3.80)	(-1.32)	(-1.60)	(-3.54)
	Diff.	3.85	4.15	1.60	0.80	0.60	2.45
		(6.70)	(4.20)	(1.55)	(0.75)	(0.55)	(2.70)
oibtrd	High A_Search	2.35	1.10	-0.20	-0.20	0.20	0.15
		(7.23)	(1.90)	(-0.32)	(-0.35)	(0.35)	(0.31)
	Low A_Search	-0.95	-2.05	-1.80	-1.00	-0.85	-0.80
		(-2.60)	(-3.20)	(-2.88)	(-1.53)	(-1.30)	(-1.43)
	Diff.	3.35	3.15	1.60	0.80	1.05	0.95
		(6.70)	(3.65)	(1.85)	(0.90)	(1.20)	(1.25)
		Insider Purchase Opportunistic Event Window					
oibvol	High A_Search	2.30	2.25	-2.40	-0.50	-3.00	0.20
		(3.05)	(1.84)	(-1.74)	(-0.32)	(-2.03)	(0.18)
	Low A_Search	-0.40	-0.90	-3.60	-0.15	-0.50	-0.90
		(-0.47)	(-0.57)	(-2.29)	(-0.08)	(-0.30)	(-0.62)
	Diff.	2.70	3.15	1.20	-0.35	-2.50	1.10
		(2.30)	(1.60)	(0.55)	(-0.15)	(-1.15)	(0.60)
oibtrd	High A_Search	2.90	1.35	-0.75	0.65	-1.20	0.55
		(4.38)	(1.27)	(-0.60)	(0.49)	(-0.94)	(0.51)
	Low A_Search	0.50	-1.30	-2.05	0.50	-0.20	0.80
		(0.63)	(-0.96)	(-1.54)	(0.36)	(-0.14)	(0.67)
	Diff.	2.45	2.65	1.30	0.15	-1.00	-0.25
		(2.40)	(1.55)	(0.70)	(0.10)	(-0.55)	(-0.15)
		Insider Purchase Routine Event Window					
oibvol	High A_Search	0.60	0.25	3.65	-7.75	-2.85	2.00
		(0.27)	(0.07)	(0.93)	(-1.82)	(-0.69)	(0.56)
	Low A_Search	-4.80	-6.10	-6.35	3.75	-7.00	-4.00
		(-2.21)	(-1.63)	(-1.86)	(0.93)	(-1.96)	(-1.36)
	Diff.	5.40	6.35	10.00	-11.50	4.15	6.00
		(1.70)	(1.25)	(1.95)	(-1.95)	(0.75)	(1.30)
oibtrd	High A_Search	0.95	1.40	4.70	-1.10	1.65	4.00
		(0.48)	(0.47)	(1.38)	(-0.30)	(0.44)	(1.42)
	Low A_Search	-3.15	-1.35	-3.65	-2.05	-5.30	-2.10
		(-1.76)	(-0.47)	(-1.33)	(-0.66)	(-1.85)	(-0.82)
	Diff.	4.05	2.75	8.35	0.95	6.95	6.10
		(1.55)	(0.65)	(1.95)	(0.20)	(1.50)	(1.60)

Table 4: Following Insider Trading: Panel Regressions

This table reports results of panel regressions of retail order imbalance of stock i in week t on the same-week insider trading dummies (Models (1) - (4)) and retail order imbalance of stock i in week $t+1$ on the prior-week insider trading dummies (Models (5) - (8)), all in the insider-trading universe. We construct insider trading dummy variables as an insider buy dummy (Buy), an opportunistic buy dummy (Opp_Buy), an opportunistic sell dummy (Opp_Sell), a routine buy dummy (Rou_Buy), and a routine sell dummy (Rou_Sell). The dummies equal one if the stock in week t has such an insider trade. In Model (1) and Model (2), the dependent variable is $oibvol_t$, as defined in Table 1. The dependent variable in Model (3) and Model (4) is $oibtrd_t$, as defined in Table 1. The dependent variables in Models (5) - (8) with subscript $t+1$ represent the corresponding one-week-ahead order imbalance. The main independent variables include Buy in Model (1), (3), (5) and (7), Opp_Buy, Rou_Buy, Opp_Sell, and Rou_Sell in Model (2), (4), (6) and (8). We include firm size (LSIZE), book-to-market ratio (LBM), turnover (TURN), idiosyncratic volatility (IVOL), momentum (MOM), short-term reversal (RET1), prior week return (RET1W), investor attention (ATT) as well as retail investor attention (ASVI) as control variables. The sample period is from January 2010 to December 2018. We include week fixed effects in all specifications. Standard errors are two-way clustered at the firm and the week level. *p<0.1; **p<0.05, ***p<0.01.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variable	$\mathrm{oibvol_t}$	$\mathrm{oibvol_t}$	$\mathrm{oibtrd_t}$	$\mathrm{oibtrd_t}$	$\mathrm{oibvol_{t+1}}$	$\mathrm{oibvol_{t+1}}$	$\mathrm{oibtrd_{t+1}}$	$\mathrm{oibtrd_{t+1}}$
Opp_Buy		0.104***		0.118***		0.074***		0.071***
		(4.42)		(5.78)		(3.48)		(3.58)
Rou_Buy		-0.002		0.033		-0.010		0.053
		(-0.03)		(0.48)		(-0.18)		(0.80)
Opp_Sell		-0.004		-0.007		0.001		-0.012*
		(-0.57)		(-0.96)		(0.10)		(-1.66)
Rou_Sell		-0.008		-0.017		-0.026*		-0.026*
		(-0.53)		(-1.07)		(-1.92)		(-1.79)
LSIZE	0.020***	0.016***	0.024***	0.021***	0.014***	0.011***	0.020***	0.018***
	(5.92)	(4.69)	(6.56)	(5.72)	(4.16)	(3.35)	(5.44)	(4.86)
LBM	-0.027***	-0.021***	-0.027***	-0.023***	-0.023***	-0.020***	-0.027***	-0.024***
	(-4.82)	(-3.79)	(-4.77)	(-3.98)	(-4.39)	(-3.70)	(-4.89)	(-4.31)
TURN	0.084***	0.067***	0.020	0.007	0.095***	0.083***	0.008	-0.002
	(3.43)	(2.68)	(0.78)	(0.25)	(4.08)	(3.51)	(0.30)	(-0.07)
IVOL	3.410***	3.849***	2.133***	2.499***	1.981***	2.292***	1.410***	1.670***
	(6.71)	(7.53)	(4.39)	(5.14)	(4.35)	(5.00)	(3.07)	(3.64)
MOM	-0.021	-0.038***	0.012	-0.002	-0.008	-0.020	0.024*	0.012
	(-1.53)	(-2.70)	(0.86)	(-0.14)	(-0.59)	(-1.45)	(1.77)	(0.92)
RET1	-0.079**	-0.118***	-0.064**	-0.097***	-0.016	-0.044	0.018	-0.008
	(-2.51)	(-3.76)	(-2.11)	(-3.21)	(-0.50)	(-1.34)	(0.58)	(-0.25)
RET1W	-2.335***	-2.655***	-2.085***	-2.349***	-1.127***	-1.351***	-1.365***	-1.575***
	(-7.70)	(-8.73)	(-7.56)	(-8.48)	(-3.77)	(-4.49)	(-4.85)	(-5.60)
ATT	0.046***	0.048***	0.060***	0.061***	0.028***	0.029***	0.037***	0.038***
	(12.04)	(12.45)	(16.38)	(16.69)	(7.95)	(8.27)	(11.34)	(11.66)
ASVI	0.005*	0.005*	0.003	0.003	0.000	0.000	0.002	0.002
	(1.87)	(1.90)	(1.41)	(1.40)	(0.10)	(0.12)	(1.03)	(0.98)
Buy	0.125***		0.113***		0.085***		0.085***	
	(10.45)		(9.43)		(7.09)		(7.07)	
Constant	-0.563***	-0.481***	-0.548***	-0.482***	-0.421***	-0.368***	-0.465***	-0.415***
	(-10.71)	(-9.17)	(-9.73)	(-8.64)	(-8.19)	(-7.19)	(-8.33)	(-7.50)
Observations	94,665	94,665	94,665	94,665	94,012	94,012	94,012	94,012
R-squared	0.026	0.024	0.030	0.028	0.021	0.020	0.026	0.025

Table 5: Retail Order Flow around Insider Trades - Investor Attention

This table reports results of panel regressions of retail order imbalance of stock i in week t on the same-week insider trading dummies in the insider-trading universe. We construct insider trading dummy variables as an opportunistic buy dummy (Opp_Buy), an opportunistic sell dummy (Opp_Sell), a routine buy dummy (Rou_Buy), and a routine sell dummy (Rou_Sell). The dummies equal one if the stock in week t has such an insider trade. In Models (1) and (3), the dependent variable is *oibvol*, as defined in Table 1. The dependent variable in Models (2) and (4) is *oibtrd*, as defined in Table 1. As for main independent variables, we use Opp_Buy as opportunistic buy dummy and Rou_Buy as routine buy dummy. We assign ASVI to be high when it is among the highest 33.3% of the sample, and low when it is among the lowest 33.3% of the sample. We run regressions for the sub-samples $\mathrm{ASVI_t}$ = High and $\mathrm{ASVI_t}$ = Low separately. We report the coefficient estimates for Opp_Buy and Rou_Buy as well as coefficient differences between Model (1) and Model (3), and between Model (2) and Model (4). We include firm size (LSIZE), book-to-market ratio (LBM), turnover (TURN), idiosyncratic volatility (IVOL), momentum (MOM), short-term reversal (RET1), prior week return (RET1W) as well as investor attention (ATT) as control variables. We do not report coefficients on control variables for brevity. The sample period is from January 2010 to December 2018. *p<0.1; **p<0.05, ***p<0.01.

		$\mathrm{ASVI_t}$ = High		**$\mathrm{ASVI_t}$ = Low**			
		(1)	(2)	(3)	(4)	(1) - (3)	(2) - (4)
Variable		oibvol	oibtrd	oibvol	oibtrd	oibvol	oibtrd
Opp_Buy	Coeff.	0.078***	0.103***	0.095***	0.082***	-0.017	0.021
	t-stat	(3.01)	(4.43)	(3.58)	(3.44)	(-0.47)	(0.64)
Rou_Buy	Coeff.	0.038	0.048	-0.014	-0.024	0.052	0.072
	t-stat	(0.74)	(1.03)	(-0.22)	(-0.43)	(0.65)	(1.00)
Obs.		32,364		31,159			

Table 6: Retail Order Flow around Insider Trades - Common Information

This table reports results of panel regressions of retail order imbalance of stock i in week t on the same-week insider trading dummies in the insider-trading universe. We construct insider trading dummy variables as an opportunistic buy dummy (Opp_Buy), an opportunistic sell dummy (Opp_Sell), a routine buy dummy (Rou_Buy), and a routine sell dummy (Rou_Sell). The dummies equal one if the stock in week t has such an insider trade. In Model (1) and Model (3), the dependent variable is *oibvol*, as defined in Table 1. The dependent variable in Model (2) and Model (4) is *oibtrd*, as defined in Table 1. As for main independent variables, we use Opp_Buy as opportunistic buy dummy and Rou_Buy as routine buy dummy. Panel A and B identify earnings news as one common information source. Panel C and D regard analyst information as another common source. Specifically, Panel A reports the regression results based on whether there is any upcoming earnings announcement $EA_{[t+1,\ t+4]}$ in the next month (week t+1 to week t+4). $EA_{[t+1,\ t+4]}$ equals 1 if there is earnings announcement event, and 0 otherwise. We further divide the sub-sample of $EA_{[t+1,\ t+4]} = 1$ into cases when SUE >0 and SUE <0. SUE is defined as three-day abnormal return around the earnings announcement event. Panel B reports the regression results based on whether there is a positive or negative SUE. Panel C reports the regression results for the sub-samples of recommendation upgrade and downgrade in the next month separately. We define the sub-sample as "Rec Upgrade" when the change of analyst recommendations is positive. We define the sub-sample as "Rec Downgrade" when the change of analyst recommendations is negative. The change of analyst recommendations is calculated as the next month consensus recommendation minus its value for the same stock one month ago. In Panel D, we report the regression results for the sub-samples of analyst earnings forecast up revision and down revision in the next month separately. We define the sub-sample as "Forecast Up" when the change of analyst EPS forecast is positive. We define the sub-sample as "Forecast Down" when the change of analyst EPS forecast is negative. The change of analyst EPS forecast is calculated as the next month EPS Median Estimate averaged across all analysts minus its value for the same stock one month ago. We report the coefficient estimates for Opp_Buy and Rou_Buy as well as coefficient differences between Model (1) and Model (3), and between Model (2) and Model (4). We include firm size (LSIZE), book-to-market ratio (LBM), turnover (TURN), idiosyncratic volatility (IVOL), momentum (MOM), short-term reversal (RET1), prior week return (RET1W) as well as investor attention (ATT) as control variables. We do not report coefficients on control variables for brevity. The sample period is from January 2010 to December 2018. *p<0.1; **p<0.05, ***p<0.01.

Table 6 (Cont.): Retail Order Flow around Insider Trades - Common Information

Panel A: Conditions based on Upcoming Earnings Announcement Events

		$\mathbf{EA_{[t+1,\ t+4]} = 1}$		$\mathbf{EA_{[t+1,\ t+4]} = 0}$			
		(1)	(2)	(3)	(4)	(1) - (3)	(2) - (4)
Variable		oibvol	oibtrd	oibvol	oibtrd	oibvol	oibtrd
Opp_Buy	Coeff.	0.024	0.083**	0.113***	0.111***	-0.089*	-0.028
	t-stat	(0.53)	(2.02)	(6.98)	(7.68)	(-1.84)	(-0.65)
Rou_Buy	Coeff.	-0.164**	-0.038	-0.013	0.001	-0.151**	-0.040
	t-stat	(-2.51)	(-0.65)	(-0.35)	(0.04)	(-2.01)	(-0.59)
Obs.		12,538		81,860			

Panel B: Conditions based on Upcoming Good/Bad Earnings News

		SUE >0		**SUE <0**			
		(1)	(2)	(3)	(4)	(1) - (3)	(2) - (4)
Variable		oibvol	oibtrd	oibvol	oibtrd	oibvol	oibtrd
Opp_Buy	Coeff.	0.137**	0.187***	0.046	0.048	0.091	0.139
	t-stat	(2.00)	(3.03)	(0.68)	(0.74)	(0.94)	(1.56)
Rou_Buy	Coeff.	0.195**	0.207**	-0.304***	-0.093	0.499***	0.300**
	t-stat	(2.01)	(2.36)	(-3.04)	(-0.98)	(3.58)	(2.33)
Obs.		6,080		5,826			

Panel C: Upcoming Analyst Recommendation Update

		Rec Upgrade		**Rec Downgrade**			
		(1)	(2)	(3)	(4)	(1) - (3)	(2) - (4)
Variable		oibvol	oibtrd	oibvol	oibtrd	oibvol	oibtrd
Opp_Buy	Coeff.	0.063**	0.094***	0.126***	0.099***	-0.063	-0.005
	t-stat	(2.23)	(3.59)	(4.39)	(3.75)	(-1.57)	(-0.13)
Rou_Buy	Coeff.	-0.001	0.037	-0.100	-0.128*	0.099	0.164*
	t-stat	(-0.02)	(0.59)	(-1.37)	(-1.89)	(1.00)	(1.79)
Obs.		27,261		27,256			

Panel D: Upcoming Analyst Forecast Revision

		Forecast Up		**Forecast Down**			
		(1)	(2)	(3)	(4)	(1) - (3)	(2) - (4)
Variable		oibvol	oibtrd	oibvol	oibtrd	oibvol	oibtrd
Opp_Buy	Coeff.	0.087***	0.110***	0.139***	0.136***	-0.052	-0.026
	t-stat	(3.83)	(5.34)	(6.18)	(6.64)	(-1.63)	(-0.89)
Rou_Buy	Coeff.	-0.036	0.009	-0.033	0.037	-0.002	-0.028
	t-stat	(-0.74)	(0.20)	(-0.68)	(0.83)	(-0.03)	(-0.45)
Obs.		48,600		37,738			

Table 7: Cumulative Market-adjusted Returns Based on Retail Order Flow within Opportunistic Insider Purchase Window

This table reports the cumulative market-adjusted stock returns up to 52 weeks after opportunistic insider purchase, based on whether retail investors trade on the same side with opportunistic insiders (Follow or Not-Follow). The bottom row reports the difference between these two groups in the future cumulative market-adjusted returns. Specifically, we divide the sample into two sub-samples based on whether retail investor purchase or sell the stock that opportunistic insider bought in the event week (from the opportunistic insider buy date to one day after the SEC filing date of this trade). The sub-sample "Follow" include stocks with positive retail order imbalance *oibvol* during the event week, and "Not-Follow" include those with negative retail order imbalance *oibvol* during the event week. We present next-week returns as well as cumulative returns for next 4 weeks, 12 weeks, 18 weeks, 24 weeks and 52 weeks, respectively. We use CRSP daily value-weighted market returns to calculate the average weekly market return, and subtract it from weekly stock return to get the weekly market-adjusted return. Standard errors are clustered at the week level. The returns are shown in percent. *p<0.1; **p<0.05, ***p<0.01.

Classification		Time Periods					
		Week 1	Week 1-4	Week 1–12	Week 1-18	Week 1–24	Week 1-52
Follow	Mean	0.23	0.39	0.62	0.75	0.69	0.89
	t-stat	(11.35)	(8.73)	(8.06)	(9.35)	(6.89)	(6.37)
Not-Follow	Mean	0.14	0.24	0.40	0.57	0.52	0.79
	t-stat	(7.55)	(6.25)	(5.56)	(7.55)	(5.13)	(5.83)
Follow − Not-Follow	Mean	0.10***	0.15***	0.22**	0.18*	0.18	0.10
	t-stat	(3.55)	(3.16)	(2.36)	(1.65)	(1.48)	(0.50)

Table 8: Calendar-Week Portfolio Analysis

This table reports the weekly alphas for the retail Follow portfolio and Not-Follow portfolio, as well as those for the long-short portfolio (Follow - Not-Follow). For the sub-sample of stocks with opportunistic insider purchases, we further divide it into two sub-samples based on whether retail investor purchase or sell those stocks during the event week (from the opportunistic insider buy date to one day after the SEC filing date of this trade). The Follow portfolio includes stocks with positive retail order imbalance *oibvol* in the event week, and the Not-Follow portfolio includes stocks with negative retail order imbalance *oibvol* in the event week. We rebalance the portfolio every week (Panel A) or every four weeks (Panel B). For each portfolio, we calculate the equal-weighted weekly returns, the CAPM alphas, the Fama and French (1993) three-factor alphas, and the Carhart (1997) four-factor alphas. The sample period is from January 2010 to December 2018. The returns and alphas are shown in percent. *p<0.1; **p<0.05, ***p<0.01.

Panel A: Equal-Weighted Portfolio Returns for Next Calendar Week

	Follow	Not-Follow	Follow – Not-Follow
Raw Return	0.268***	0.195***	0.079**
	(7.13)	(5.76)	(2.16)
CAPM Alpha	0.201***	0.133***	0.073**
	(6.75)	(4.90)	(2.01)
Carhart Alpha	0.211***	0.140***	0.079**
	(7.48)	(5.36)	(2.15)

Panel B: Equal-Weighted Portfolio Weekly Returns for 4-Week Holding Period

	Follow	Not-Follow	Follow – Not-Follow
Raw Return	0.175***	0.114***	0.052**
	(5.07)	(3.78)	(2.45)
CAPM Alpha	0.097***	0.054**	0.036*
	(3.77)	(2.41)	(1.70)
Carhart Alpha	0.106***	0.065***	0.036*
	(4.35)	(3.18)	(1.68)

Table 9: Return Predictability of Retail Purchases Following Insider Purchases: Panel Regressions

This table reports the panel regression results of one-week ahead return of stock i from week t (Ret_{t+1}) on insider trading and retail trading indicators. In the first three models, we include three dummy variables: opportunistic insider purchase (Opp_Buy), routine insider purchase (Rou_Buy), as defined in Table 4, and retail investor purchase (Retail_Buy). Retail_Buy equals 1 if retail investors buy the stock, and 0 if they sell the stock. We also include interaction terms Opp_Buy * Retail_Buy and Rou_Buy * Retail_Buy. Model (4) only includes stocks with opportunistic insider purchases. We include an additional dummy variable Follow_Oppbuy, which equals 1 if retail investors buy the stock during the week, and 0 otherwise. In all models we include firm size (LSIZE), book-to-market ratio (LBM), turnover (TURN), idiosyncratic volatility (IVOL), momentum (MOM), short-term reversal (RET1), prior week return (RET1W), investor attention (ATT) as well as retail investor attention (ASVI) as control variables. The sample period is from January 2010 to December 2018. We include week fixed effects in all models. Standard errors are two-way clustered at the firm and the week level in all models. *p<0.1; **p<0.05, ***p<0.01.

	(1)	(2)	(3)	(4)
Variable	RET_{t+1}	RET_{t+1}	RET_{t+1}	RET_{t+1}
LSIZE	0.0001***	0.0001***	0.0001***	0.0002*
	(5.01)	(4.93)	(5.00)	(1.69)
LBM	-0.0004***	-0.0004***	-0.0004***	-0.0002
	(-8.97)	(-8.93)	(-8.95)	(-0.80)
TURN	-0.0017***	-0.0017***	-0.0017***	-0.0025*
	(-6.49)	(-6.49)	(-6.48)	(-1.82)
IVOL	0.0737***	-0.0074	-0.0075	-0.0075
	(2.94)	(-1.55)	(-1.58)	(-1.57)
MOM	-0.0003	-0.0003	-0.0003	-0.0019*
	(-1.59)	(-1.56)	(-1.55)	(-1.89)
RET1	-0.0008*	-0.0008*	-0.0008*	0.0028
	(-1.77)	(-1.78)	(-1.76)	(1.23)
RET1W	-0.0096**	-0.0095**	-0.0093**	-0.0119
	(-2.46)	(-2.42)	(-2.38)	(-0.60)
ATT	0.0001***	0.0001***	0.0001***	0.0003*
	(3.83)	(3.76)	(3.65)	(1.73)
ASVI	0.0001***	0.0001***	0.0001***	-0.0002
	(6.66)	(6.61)	(6.62)	(-1.26)
Opp_Buy	0.0013***		0.0009***	
	(7.25)		(3.83)	
Rou_Buy	0.0003		0.0005	
	(0.80)		(0.89)	
Retail_Buy		0.0002***	0.0002***	
		(6.47)	(6.29)	
Opp_Buy * Retail_Buy			0.0007**	
			(2.04)	
Rou_Buy * Retail_Buy			-0.0004	
			(-0.75)	
Follow_Oppbuy				0.0007**
				(1.98)
Constant	-0.0014***	-0.0015***	-0.0015***	-0.0027
	(-3.52)	(-3.64)	(-3.72)	(-1.38)
Observations	597,422	596,168	596,168	3,840
R-squared	0.189	0.189	0.189	0.292

Table 10: Decomposition of Retail Order Imbalance

This table reports the second-stage regression results of a two-stage retail order imbalance decomposition analysis. We follow Boehmer et al. (2021) and decompose retail order imbalance into persistence, contrarian, and other (information) components. The decomposition is done through two-stage regressions. For the first stage, we estimate the following regression model:

$$\text{Retail\_Buy}^{i}{}_{t} = a_t + b_t{*}\text{Retail\_Buy}^{i}{}_{t\text{-}1} + c_t{*}\text{Ret}^{i}{}_{t\text{-}1} + \epsilon^{i}{}_{t}$$

Retail_Buy_Persistence is then defined as $\widehat{b_t} * \textit{Retail\_Buy}^{i}{}_{t\text{-}1}$ and Retail_Buy_Contrarian is defined as $\widehat{c_t} * \textit{Ret}^{i}{}_{t\text{-}1}$, where $\widehat{b_t}$ and $\widehat{c_t}$ are the estimated coefficients of the first-stage regression. The residual part from the first-stage regression is denoted as Retail_Buy_Other. In the second stage, we run panel regressions similar to Table 9, except that we replace Retail_Buy with the three components that are computed in the first stage. We include the same set of control variables as in Table 9. The coefficient estimates for those variables are not reported for brevity. We include week fixed effects for all models. Standard errors are two-way clustered at the firm and the week level in all models. *p<0.1; **p<0.05, ***p<0.01.

Variable	(1) RET_{t+1}	(2) RET_{t+1}	(3) RET_{t+1}	(4) RET_{t+1}
Retail_Buy_Persistence	0.0010***	0.0011***	0.0011***	0.0088
	(5.31)	(5.40)	(5.34)	(0.51)
Retail_Buy_Contrarian	-0.0051	-0.0050	-0.0051	0.0340
	(-1.16)	(-1.16)	(-1.17)	(1.12)
Retail_Buy_Other	0.0002***	0.0002***	0.0002***	0.0078
	(5.72)	(5.91)	(5.73)	(0.44)
Opp_Buy	0.0012***		0.0012***	
	(5.01)		(4.97)	
Rou_Buy		0.0006	0.0006	
		(1.39)	(1.24)	
Opp_Buy * Retail_Buy_Persistence	-0.0000		0.0000	
	(-0.02)		(0.01)	
Opp_Buy * Retail_Buy_Contrarian	0.0069		0.0065	
	(0.56)		(0.53)	
Opp_Buy * Retail_Buy_Other	0.0007**		0.0007**	
	(2.06)		(2.07)	
Rou_Buy * Retail_Buy_Persistence		-0.0046	-0.0048	
		(-1.28)	(-1.33)	
Rou_Buy * Retail_Buy_Contrarian		0.0385	0.0372	
		(1.58)	(1.54)	
Rou_Buy * Retail_Buy_Other		-0.0003	-0.0004	
		(-0.54)	(-0.59)	
Follow_Oppbuy				-0.0171
				(-0.90)
Follow_Oppbuy * Retail_Buy_Persistence				0.0013
				(1.62)
Follow_Oppbuy * Retail_Buy_Contrarian				0.0069
				(0.30)
Follow_Oppbuy * Retail_Buy_Other				0.0170**
				(2.55)
Controls	Yes	Yes	Yes	Yes
Observations	597,422	596,168	596,168	3,840
R-squared	0.189	0.189	0.189	0.292

Table 11: Cumulative Market-adjusted Returns on Stocks Traded by Retail Investors Following Insider Trading: The Effect of Information Asymmetry

This table reports the effect of retail investors following opportunistic insider purchases on market-adjusted returns for stocks with different levels of information asymmetry. We use firm size (Panel A), idiosyncratic volatility (Panel B) as well as Amihud illiquidity (Panel C) as proxies for information asymmetry. In each panel we further separate the sample stocks into Follow portfolio and Not-Follow portfolio, based on whether retail investors follow insiders as defined in Table 1. In each panel, we categorize the sample of stocks into three levels of information asymmetry. For each level, we compute the difference in the cumulative market-adjusted returns between Follow portfolio and Not-Follow portfolio, up to 24 weeks. We use CRSP daily value-weighted market returns to calculate the average weekly market return, and subtract it from weekly stock return to get the weekly market-adjusted return. Standard errors are clustered at the week level. The returns are shown in percent. *p<0.1; **p<0.05, ***p<0.01.

Panel A: Sort by Firm Size

Classification			Time Periods		
			Week 1 – Week 4	Week 1 – Week 12	Week 1 – Week 24
Small	Follow –	Mean	0.26**	0.56***	0.57**
	Not-Follow	t-stat	(2.43)	(2.73)	(1.98)
Mid-Cap	Follow –	Mean	0.16**	0.17	0.23
	Not-Follow	t-stat	(2.08)	(1.28)	(1.24)
Large	Follow –	Mean	0.03	-0.04	-0.20
	Not-Follow	t-stat	(0.48)	(-0.32)	(-1.02)
Small – Large	Diff. in Diff.	Mean	0.23*	0.60**	0.77**
		t-stat	(1.73)	(2.53)	(2.16)

Panel B: Sort by Idiosyncratic Volatility

Classification			Time Periods		
			Week 1 – Week 4	Week 1 – Week 12	Week 1 – Week 24
Low	Follow –	Mean	0.08*	0.22***	0.22*
	Not-Follow	t-stat	(1.67)	(2.65)	(1.88)
Mid	Follow –	Mean	0.08	0.07	0.08
	Not-Follow	t-stat	(1.55)	(0.72)	(0.55)
High	Follow –	Mean	0.38**	0.57*	0.49
	Not-Follow	t-stat	(2.19)	(1.72)	(1.15)
High – Low	Diff. in Diff.	Mean	0.61**	0.30	0.25
		t-stat	(1.97)	(0.73)	(0.35)

Panel C: Sort by Amihud Illiquidity

Classification			Time Periods		
			Week 1 – Week 4	Week 1 – Week 12	Week 1 – Week 24
Low	Follow –	Mean	0.02	0.03	-0.22
	Not-Follow	t-stat	(0.35)	(0.22)	(-1.15)
Mid	Follow –	Mean	0.20**	0.08	0.28
	Not-Follow	t-stat	(2.34)	(0.52)	(1.41)
High	Follow –	Mean	0.24**	0.52***	0.48*
	Not-Follow	t-stat	(2.30)	(2.65)	(1.74)
High – Low	Diff. in Diff.	Mean	0.22*	0.49**	0.69**
		t-stat	(1.66)	(2.17)	(2.10)

Table 12: Improvement of Informational Efficiency: Variance Ratio and Price Delay Measure

This table reports the regression results of proxies for informational efficiency on the insider and retail trading dummies in insider-trading event week. In Models (1)-(4), the dependent variables are $|1-VR(n,m)|$, where VR(n,m) represents variance ratios of the m-day return variance per unit time divided by the n-day return variance per unit time estimated, using daily returns next month. In Models (5)-(6), the dependent variables are Prc_dalay, which is the monthly price delay measure of Boehmer and Wu (2013). We include dummy variables for opportunistic insider purchase (Opp_Buy), routine insider purchase (Rou_Buy), retail investor purchase (Retail_Buy), all as defined in the previous tables, as well as interaction terms Opp_Buy * Retail_Buy and Rou_Buy * Retail_Buy. We also include the dummy variable Follow_Oppbuy as defined in Table 9. We include firm size (LSIZE), book-to-market ratio (LBM), turnover (TURN), idiosyncratic volatility (IVOL), momentum (MOM), short-term reversal (RET1), prior week return (RET1W), investor attention (ATT) as well as retail investor attention (ASVI) as control variables. The sample period is from January 2010 to December 2018. We include week fixed effects in all models. Standard errors are two-way clustered at the firm and the week level in all models. *p<0.1; **p<0.05, ***p<0.01.

	(1)	(2)	(3)	(4)	(5)	(6)
Variable	$\lvert 1-VR(1,10)\rvert$	$\lvert 1-VR(1,10)\rvert$	$\lvert 1-VR(1,20)\rvert$	$\lvert 1-VR(1,20)\rvert$	Prc_delay	Prc_delay
LSIZE	-0.0054***	-0.0019	0.0061***	0.0270***	-0.5637*	0.2342
	(-20.90)	(-0.64)	(8.94)	(3.44)	(-1.82)	(0.68)
LBM	-0.0004	0.0023	-0.0056***	0.0019	-0.2109	0.1404
	(-0.89)	(0.42)	(-4.80)	(0.13)	(-1.24)	(1.07)
TURN	-0.0152***	-0.0530**	0.0505***	-0.0736	-0.3373	-1.0020
	(-6.40)	(-2.02)	(8.08)	(-0.99)	(-0.29)	(-1.03)
IVOL	0.1908***	0.2333	0.7492***	4.8782***	-28.7695	23.8709
	(5.14)	(0.55)	(7.64)	(4.23)	(-0.92)	(0.86)
MOM	-0.0106***	0.0028	-0.0337***	0.0006	-0.4398	-0.8253
	(-8.09)	(0.18)	(-9.74)	(0.01)	(-0.82)	(-1.09)
RET1	-0.0058*	0.0528	-0.0309***	0.1871*	0.0219	2.7605*
	(-1.74)	(1.38)	(-3.52)	(1.86)	(0.01)	(1.81)
RET1W	-0.0854**	-0.5177	-0.0071	-0.6297	-8.8123	-6.0013
	(-2.48)	(-1.39)	(-0.08)	(-0.65)	(-0.25)	(-0.81)
ATT	-0.0084***	-0.0097***	-0.0120***	-0.0060	0.8473	-0.0754
	(-23.92)	(-2.58)	(-12.75)	(-0.59)	(1.18)	(-0.50)
ASVI	-0.0002	-0.0031	-0.0009	0.0034	0.1477	-0.2716
	(-0.86)	(-1.01)	(-1.28)	(0.41)	(0.69)	(-1.13)
Opp_Buy	0.0022		0.0163		-0.7189	
	(0.39)		(1.07)		(-0.80)	
Rou_Buy	0.0106		-0.0100		1.1249	
	(0.87)		(-0.30)		(1.15)	
Retail_Buy	-0.0001		-0.0009		-0.5452	
	(-0.12)		(-0.49)		(-0.65)	
Opp_Buy * Retail_Buy	-0.0145*		-0.0459**		-0.4369	
	(-1.82)		(-2.19)		(-0.35)	
Rou_Buy * Retail_Buy	-0.0105		-0.0353		-0.7011	
	(-0.58)		(-0.74)		(-0.62)	
Follow_Oppbuy		-0.0169**		-0.0561**		-1.3602*
		(-2.05)		(-2.55)		(-1.69)
Constant	0.3940***	0.3598***	0.5393***	0.1660	8.5126	-2.0107
	(101.80)	(8.60)	(52.58)	(1.50)	(1.56)	(-0.49)
Observations	596,896	3,853	596,866	3,853	498,951	3,163
R-squared	0.031	0.145	0.074	0.148	0.001	0.472

Table 13: Following Insider Trading: Longer Horizons

This table reports results of panel regressions of both retail order imbalance and changes of institutional ownership of stock i from quarter t to quarter $t+4$ on the insider trading dummies in quarter t in the insider-trading universe. We construct insider trading dummy variables same as in Table 4. In Panel A, the dependent variables are $oibvol_t$, $oibvol_{t+1}$, $oibvol_{t+2}$, $oibvol_{t+3}$, $oibvol_{t+4}$, which are the quarterly retail order imbalance in the subsequent four quarters, for the stocks that insiders purchased. In Panel B, the dependent variables are ΔIO_t, ΔIO_{t+1}, ΔIO_{t+2}, ΔIO_{t+3}, ΔIO_{t+4}, which are the quarterly changes of institutional ownership in the subsequent four quarters, for the stocks that insiders purchased. The main independent variables include Buy in odd-number models, Opp_Buy, Rou_Buy, Opp_Sell, and Rou_Sell in even-number models. We include firm size (LSIZE), book-to-market ratio (LBM), turnover (TURN), idiosyncratic volatility (IVOL), momentum (MOM), short-term reversal (RET1), prior week return (RET1W), investor attention (ATT) as well as retail investor attention (ASVI) as control variables. The sample period is from January 2010 to December 2018. We include week fixed effects in all specifications. Standard errors are two-way clustered at the firm and the week level. *p<0.1; **p<0.05, ***p<0.01.

Panel A: Retail Order Imbalance

Variable	(1) $oibvol_t$	(2) $oibvol_t$	(3) $oibvol_{t+1}$	(4) $oibvol_{t+1}$	(5) $oibvol_{t+2}$	(6) $oibvol_{t+2}$	(7) $oibvol_{t+3}$	(8) $oibvol_{t+3}$	(9) $oibvol_{t+4}$	(10) $oibvol_{t+4}$
Opp_Buy		0.051***		0.004		0.019		0.012		0.006
		(3.38)		(0.23)		(1.16)		(0.69)		(0.36)
Rou_Buy		0.002		-0.007		-0.009		0.025		-0.001
		(0.06)		(-0.17)		(-0.24)		(0.62)		(-0.04)
Opp_Sell		-0.003		-0.005		0.000		0.004		0.006
		(-0.56)		(-0.82)		(0.08)		(0.61)		(1.00)
Rou_Sell		-0.005		-0.018*		-0.020*		-0.018		-0.019
		(-0.53)		(-1.68)		(-1.72)		(-1.56)		(-1.57)
LSIZE	0.017***	0.015***	0.016***	0.016***	0.015***	0.014***	0.013***	0.012***	0.012***	0.012***
	(5.91)	(5.15)	(5.84)	(5.78)	(5.13)	(5.03)	(4.38)	(4.26)	(4.19)	(3.98)
LBM	-0.019***	-0.016***	-0.016***	-0.016***	-0.018***	-0.017***	-0.025***	-0.025***	-0.023***	-0.022***
	(-4.10)	(-3.35)	(-3.47)	(-3.33)	(-3.62)	(-3.48)	(-5.12)	(-4.99)	(-4.50)	(-4.26)
TURN	0.107***	0.095***	0.077***	0.074***	0.065***	0.062**	0.053**	0.051**	0.066***	0.063***
	(5.05)	(4.38)	(3.58)	(3.43)	(2.71)	(2.57)	(2.07)	(2.00)	(2.74)	(2.60)
IVOL	2.611***	2.940***	2.169***	2.239***	1.654***	1.750***	0.924**	1.022**	1.075**	1.202***
	(6.10)	(6.77)	(5.04)	(5.18)	(3.66)	(3.89)	(2.04)	(2.28)	(2.47)	(2.78)
MOM	-0.009	-0.020*	0.013	0.009	0.020*	0.017	0.033***	0.030***	0.031***	0.028**
	(-0.86)	(-1.95)	(1.19)	(0.89)	(1.82)	(1.54)	(2.95)	(2.72)	(2.83)	(2.50)
RET1	-0.048**	-0.077***	0.012	0.004	0.019	0.011	0.024	0.016	0.057**	0.048**
	(-2.17)	(-3.48)	(0.54)	(0.20)	(0.86)	(0.50)	(1.05)	(0.71)	(2.55)	(2.17)
RET1W	0.229	0.137	-0.106	-0.134	-0.004	-0.033	0.199	0.168	0.167	0.127
	(1.37)	(0.82)	(-0.62)	(-0.79)	(-0.02)	(-0.20)	(1.19)	(1.01)	(0.96)	(0.73)
ATT	0.025***	0.026***	0.011***	0.011***	0.010***	0.010***	0.011***	0.011***	0.003	0.003
	(9.76)	(10.10)	(4.59)	(4.67)	(4.33)	(4.44)	(4.41)	(4.53)	(1.09)	(1.21)
ASVI	0.001	0.001	0.002	0.002	0.001	0.001	0.001	0.001	0.004**	0.004**
	(0.44)	(0.50)	(0.98)	(0.95)	(0.72)	(0.71)	(0.59)	(0.59)	(2.11)	(2.12)
Buy	0.074***		0.017*		0.020**		0.019*		0.019*	
	(7.34)		(1.76)		(1.97)		(1.71)		(1.83)	
Constant	-0.458***	-0.412***	-0.419***	-0.409***	-0.382***	-0.374***	-0.347***	-0.338***	-0.351***	-0.340***
	(-10.12)	(-9.18)	(-9.68)	(-9.55)	(-8.86)	(-8.70)	(-7.83)	(-7.72)	(-7.76)	(-7.53)
Observations	57,490	57,490	57,206	57,206	56,858	56,858	56,060	56,060	53,368	53,368
R-squared	0.055	0.052	0.042	0.042	0.040	0.040	0.044	0.044	0.044	0.044

Table 13 (Cont.): Following Insider Trading: Longer Horizons

Panel B: Changes in Institutional Ownership

Variable	(1) ΔIO_t	(2) ΔIO_t	(3) ΔIO_{t+1}	(4) ΔIO_{t+1}	(5) ΔIO_{t+2}	(6) ΔIO_{t+2}	(7) ΔIO_{t+3}	(8) ΔIO_{t+3}	(9) ΔIO_{t+4}	(10) ΔIO_{t+4}
Opp_Buy		-0.005***		-0.005***		-0.004**		-0.001		0.001
		(-2.76)		(-2.95)		(-2.07)		(-0.54)		(0.61)
Rou_Buy		-0.002		-0.004		0.001		0.002		-0.001
		(-0.56)		(-1.44)		(0.45)		(0.63)		(-0.17)
Opp_Sell		-0.004***		-0.002***		-0.003***		-0.002**		-0.003***
		(-5.16)		(-2.70)		(-3.92)		(-2.50)		(-2.86)
Rou_Sell		-0.004***		-0.003**		-0.002		-0.001		-0.001
		(-3.64)		(-2.24)		(-1.62)		(-1.10)		(-1.01)
LSIZE	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.001***	-0.001***
	(-5.12)	(-4.23)	(-5.89)	(-5.33)	(-7.83)	(-7.24)	(-5.94)	(-5.50)	(-4.99)	(-4.49)
LBM	-0.003***	-0.003***	-0.003***	-0.003***	-0.004***	-0.004***	-0.003***	-0.003***	-0.002***	-0.002***
	(-3.37)	(-3.96)	(-4.84)	(-5.28)	(-6.19)	(-6.64)	(-4.19)	(-4.50)	(-3.51)	(-3.78)
TURN	-0.002	-0.001	-0.009*	-0.008*	-0.010***	-0.010***	-0.009**	-0.009**	-0.011***	-0.011**
	(-0.29)	(-0.10)	(-1.85)	(-1.74)	(-2.78)	(-2.66)	(-2.31)	(-2.23)	(-2.61)	(-2.57)
IVOL	0.401***	0.360***	0.283***	0.260***	0.234***	0.213***	0.243***	0.226***	0.181***	0.167***
	(5.29)	(4.79)	(4.38)	(4.08)	(4.10)	(3.78)	(3.69)	(3.49)	(2.81)	(2.63)
MOM	0.018***	0.018***	0.017***	0.017***	0.009***	0.009***	0.005**	0.006***	0.004**	0.004**
	(7.49)	(7.81)	(8.29)	(8.55)	(4.80)	(4.91)	(2.53)	(2.61)	(2.47)	(2.54)
RET1	0.038***	0.040***	0.015***	0.016***	0.015***	0.015***	0.014***	0.015***	0.008**	0.008**
	(7.84)	(8.14)	(3.92)	(4.30)	(4.44)	(4.67)	(3.21)	(3.39)	(2.16)	(2.26)
RET1W	0.057	0.065	0.028	0.032	0.033	0.036	0.013	0.016	0.019	0.022
	(1.35)	(1.54)	(0.96)	(1.09)	(1.31)	(1.45)	(0.41)	(0.49)	(0.72)	(0.81)
ATT	0.004***	0.004***	0.002***	0.002***	0.001**	0.001**	0.001**	0.001**	-0.000	-0.000
	(9.39)	(9.22)	(4.79)	(4.65)	(2.45)	(2.35)	(2.37)	(2.28)	(-0.14)	(-0.21)
ASVI	-0.001*	-0.001**	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(-1.95)	(-2.15)	(-1.20)	(-1.30)	(-1.42)	(-1.56)	(-1.37)	(-1.47)	(-1.13)	(-1.24)
Buy	-0.005***		-0.003***		-0.002*		-0.001		-0.000	
	(-3.28)		(-3.01)		(-1.80)		(-0.94)		(-0.06)	
Constant	0.023***	0.019***	0.027***	0.024***	0.031***	0.030***	0.025***	0.023***	0.020***	0.019***
	(4.02)	(3.41)	(5.25)	(4.86)	(6.92)	(6.62)	(4.85)	(4.65)	(4.38)	(4.17)
Observations	50,610	50,610	50,421	50,421	50,263	50,263	50,032	50,032	49,382	49,382
R-squared	0.067	0.067	0.072	0.072	0.070	0.070	0.052	0.052	0.045	0.045

Appendix

Table A1: Lag in Days between Insider Trading Date and SEC Filing Date

This table presents summary statistics for the number of days between insider trading and their reporting the trades to the SEC.

Lag (in days)	0	1	2	3	4	5	>5
Number of Observations	127,082	380,011	368,907	16,900	5,316	3,019	33,577
% in sample	13.5%	40.7%	39.5%	1.8%	0.6%	0.3%	3.6%
		93.7%				6.3%	

Table A2: Retail Order Imbalance Around Insider Trading / Filing Date

This table presents summary statistics for the retail order imbalance (in percent) around insider trading date (TDATE) and filing date (FDATE) over the sample period from Jan 2010 to Dec 2018. The retail order imbalance variable (*oibvol*) is computed as the difference between the number of shares bought and sold by retail investors, divided by the total number of shares traded by retail investors. Another order imbalance variable (*oibtrd*) is computed as the difference between the number of buy trades and sell trades by retail investors, divided by the total number of trades by retail investors. Panel A presents the results for insider purchase universe and Panel B presents those for insider sale universe. We report the estimated mean with t-statistics (in parentheses). The standard errors are Newey-West adjusted.

Time Periods	[TDATE-10, TDATE-6]	[TDATE-5, TDATE-1]	TDATE	[TDATE, FDATE-1]	FDATE	[FDATE+1, FDATE+5]	[FDATE+6, FDATE+10]
Panel A: Insider Purchase Universe							
oibvol	-0.85	-0.84	0.22	0.52	0.28	-0.78	-1.19
t-stat	(-4.75)	(-4.65)	(1.00)	(2.23)	(1.27)	(-4.26)	(-6.46)
oibtrd	-0.31	-0.5	0.61	0.52	0.72	-0.08	-0.47
t-stat	(-2.01)	(-3.22)	(3.24)	(2.62)	(3.88)	(-0.48)	(-2.98)
Panel B: Insider Sale Universe							
oibvol	-2.48	-2.85	-3.16	-3.57	-3.18	-2.91	-2.70
t-stat	(-41.79)	(-46.98)	(-40.81)	(-47.13)	(-41.38)	(-47.13)	(-44.42)
oibtrd	-1.51	-1.68	-1.99	-2.19	-2.00	-1.85	-1.69
t-stat	(-29.36)	(-31.91)	(-29.99)	(-33.76)	(-30.28)	(-34.62)	(-32.2)

Table A3: Following Insider Trading: Daily-frequency Panel Regressions

This table reports results of panel regressions of retail order imbalance of stock i in day t on the same-day insider trading dummies in the insider-trading universe. We construct insider trading dummy variables as an insider buy dummy (Buy), an opportunistic buy dummy (Opp_Buy), an opportunistic sell dummy (Opp_Sell), a routine buy dummy (Rou_Buy), and a routine sell dummy (Rou_Sell). The dummies equal one if the stock in day t has such an insider trade. In Models (1) and (2), the dependent variable is *oibvol*, as defined in Table 1 except calculated in daily-frequency. The dependent variable in Model (3) and (4) is *oibtrd*, as defined in Table 1 except calculated in daily-frequency. The main independent variables include Buy in Model (1) and Model (3), Opp_Buy, Rou_Buy, Opp_Sell, and Rou_Sell in Models (2) and (4). We include firm size (LSIZE), book-to-market ratio (LBM), turnover (TURN), idiosyncratic volatility (IVOL), momentum (MOM), short-term reversal (RET1), prior week return (RET1W), investor attention (ATT) as well as retail investor attention (ASVI) as control variables. Furthermore, we add one dummy variable to indicator whether there is insider trading event in the last week (PRIOR). The sample period is from January 2010 to December 2018. We include day fixed effects in all specifications. Standard errors are two-way clustered at the firm and the day level. *p<0.1; **p<0.05, ***p<0.01.

	(1)	(2)	(3)	(4)
Variable	oibvol	oibvol	oibtrd	oibtrd
Opp_Buy		0.021***		0.016***
		(4.52)		(3.65)
Rou_Buy		0.000		0.003
		(0.02)		(0.32)
Opp_Sell		-0.003**		-0.003**
		(-1.98)		(-2.15)
Rou_Sell		-0.003		-0.004*
		(-1.12)		(-1.86)
LSIZE	0.010***	0.006***	0.016***	0.013***
	(4.38)	(2.79)	(7.43)	(6.12)
LBM	-0.006***	-0.005***	-0.007***	-0.006***
	(-2.96)	(-2.64)	(-3.81)	(-3.50)
TURN	-0.007	-0.008	-0.013*	-0.013*
	(-0.94)	(-0.98)	(-1.70)	(-1.74)
IVOL	0.279**	0.364***	0.302**	0.369***
	(2.10)	(2.73)	(2.44)	(2.97)
MOM	-0.004	-0.007**	0.003	-0.000
	(-1.32)	(-2.52)	(0.92)	(-0.08)
RET1	-0.023***	-0.033***	-0.018***	-0.026***
	(-3.29)	(-4.71)	(-2.82)	(-4.05)
RET1D	0.099***	0.089***	0.196***	0.188***
	(4.05)	(3.67)	(9.19)	(8.83)
PRIOR	0.002	0.002	0.003***	0.003***
	(1.46)	(1.36)	(2.76)	(2.70)
ATT	0.011***	0.011***	0.013***	0.013***
	(13.86)	(14.21)	(17.53)	(17.82)
Buy	0.039***		0.031***	
	(13.75)		(12.21)	
Constant	-0.201***	-0.142***	-0.278***	-0.232***
	(-6.04)	(-4.27)	(-8.90)	(-7.46)
Observations	491,314	491,314	491,314	491,314
R-squared	0.039	0.038	0.048	0.047

Table A4: Retail Order Flow around Insider Trades Conditioning on Earnings News

This table reports results of panel regressions of retail order imbalance of stock i in week t on the same-week insider trading dummies, an earnings event dummy, an earnings news type dummy and their interactions in the insider-trading universe. We construct insider trading dummy variables as an opportunistic buy dummy (Opp_Buy), an opportunistic sell dummy (Opp_Sell), a routine buy dummy (Rou_Buy), and a routine sell dummy (Rou_Sell). The dummies equal one if the stock in week t has such an insider trade. Earnings event dummy (EA) equals 1 if there is upcoming earnings announcement event next month, and 0 otherwise. Based on EA = 1 sub-sample, earnings news type dummy (Good) equals 1 if there is good earnings announcement news (SUE >0), and 0 if there is bad earnings announcement news (SUE <0). SUE is calculated as three-day abnormal return around the earnings announcement event. In Models (1) and (3), the dependent variable is *oibvol*, as defined in Table 1. The dependent variable in Model (2) and Model (4) is *oibtrd*, as defined in Table 1. We include firm size (LSIZE), book-to-market ratio (LBM), turnover (TURN), idiosyncratic volatility (IVOL), momentum (MOM), short-term reversal (RET1), prior week return (RET1W), investor attention (ATT) as well as retail investor attention (ASVI) as control variables. We do not report coefficients on control variables for brevity. The sample period is from January 2010 to December 2018. We include week fixed effects in all specifications. Standard errors are two-way clustered at the firm and the week level. *p<0.1; **p<0.05, ***p<0.01.

Variable	(1) oibvol	(2) oibtrd	(3) oibvol	(4) oibtrd
Opp_Buy	0.107***	0.109***	0.034	0.033
	(4.45)	(5.05)	(0.34)	(0.37)
Rou_Buy	-0.021	-0.005	-0.290*	-0.089
	(-0.42)	(-0.07)	(-1.79)	(-0.46)
Opp_Sell	-0.007	-0.010	-0.008	-0.011
	(-0.96)	(-1.26)	(-0.43)	(-0.61)
Rou_Sell	-0.016	-0.023	0.004	0.011
	(-1.19)	(-1.58)	(0.11)	(0.35)
EA	0.055***	0.033***		
	(4.54)	(2.91)		
Opp_Buy * EA	-0.081	-0.019		
	(-1.36)	(-0.35)		
Rou_Buy * EA	-0.134	-0.037		
	(-1.02)	(-0.30)		
SUE			-0.031*	-0.024
			(-1.90)	(-1.49)
Opp_Buy * SUE			0.080	0.146
			(0.67)	(1.38)
Rou_Buy * SUE			0.513***	0.323**
			(3.02)	(2.22)
Constant	-0.495***	-0.493***	-0.369***	-0.417***
	(-9.39)	(-8.77)	(-3.36)	(-3.73)
Controls	Yes	Yes	Yes	Yes
Observations	94,066	94,066	11,814	11,814
R-squared	0.025	0.029	0.053	0.060

Table A5: Future Returns Based on Retail Purchases Following Insider Purchases – Daily Fama-MacBeth Regressions

This table reports the Fama and MacBeth (1973) regression results of cumulative 7-day return of stock i (CUM_7_DAYS) on the same-day insider trading and retail trading indicators. We include three dummy variables: opportunistic insider purchase (Opp_Buy), routine insider purchase (Rou_Buy), and retail investor purchase (Retail_Buy). These dummy variables equal 1 if insiders or retail investors buy the stock, and 0 if they sell the stock. We also include interaction terms Opp_Buy * Retail_Buy and Rou_Buy * Retail_Buy. In all models we include firm size (LSIZE), book-to-market ratio (LBM), turnover (TURN), idiosyncratic volatility (IVOL), momentum (MOM), short-term reversal (RET1), prior week return (RET1W), investor attention (ATT), retail investor attention (ASVI) as well as dummy for prior insider trades within 5 trading days (PRIOR) as control variables. The sample period is from January 2010 to December 2018. Standard errors are Newey-West adjusted. *p<0.1; **p<0.05, ***p<0.01.

	(1)	(2)	(3)
Variable	CUM_7_DAYS	CUM_7_DAYS	CUM_7_DAYS
LSIZE	0.001***	0.001***	0.001***
	(6.31)	(6.24)	(6.33)
LBM	-0.004***	-0.004***	-0.004***
	(-17.83)	(-17.79)	(-17.83)
TURN	-0.012***	-0.012***	-0.012***
	(-8.48)	(-8.56)	(-8.54)
IVOL	0.112***	0.113***	0.113***
	(4.77)	(4.80)	(4.79)
MOM	-0.004***	-0.004***	-0.004***
	(-4.59)	(-4.60)	(-4.57)
RET1	-0.006***	-0.006***	-0.006***
	(-3.66)	(-3.65)	(-3.61)
RET1D	-0.037***	-0.037***	-0.037***
	(-9.13)	(-9.20)	(-9.20)
ATT	0.001***	0.001***	0.001***
	(8.36)	(8.34)	(8.17)
PRIOR	-0.001**	-0.000	-0.001**
	(-2.19)	(-0.78)	(-2.21)
Opp_Buy	0.014***		0.013***
	(14.33)		(11.86)
Rou_Buy	0.005***		0.005***
	(3.48)		(3.05)
Retail_Buy		0.001***	0.001***
		(13.62)	(13.39)
Opp_Buy * Retail_Buy			0.003**
			(2.17)
Rou_Buy * Retail_Buy			0.001
			(0.49)
Constant	-0.010***	-0.010***	-0.010***
	(-5.99)	(-6.16)	(-6.25)
Observations	6,417,048	6,376,598	6,376,598
R-squared	0.045	0.045	0.046
Number of groups	2,237	2,237	2,237

Table A6: Future Returns Based on Retail Order Flow within Opportunistic Insider Purchase Window – Daily Panel Regressions

This table reports the daily panel regression results of cumulative 3-day, 7-day and 10-day returns of stock i (CUM_3, CUM_7, CUM_10) on the same-day with retail investors following opportunistic insider purchases. We only include stocks with opportunistic insider purchases. We construct the dummy variable Follow_Oppbuy, which equals 1 if retail investors buy the stock during the week, and 0 otherwise. Additionally, we control for other stock characteristics in our regressions. We include firm size (LSIZE), book-to-market ratio (LBM), turnover (TURN), idiosyncratic volatility (IVOL), momentum (MOM), short-term reversal (RET1), prior week return (RET1W), investor attention (ATT), retail investor attention (ASVI) as well as dummy for prior insider trades within 5 trading days (PRIOR) as control variables. The sample period is from January 2010 to December 2018. We include day fixed effects in even-number models. Standard errors are two-way clustered at the firm and the day level in all models. *p<0.1; **p<0.05, ***p<0.01.

	(1)	(2)	(3)	(4)	(5)	(6)
Variable	CUM_3	CUM_3	CUM_7	CUM_7	CUM_10	CUM_10
LSIZE	0.001***	0.001***	0.002**	0.001**	0.002**	0.002**
	(3.01)	(2.60)	(2.30)	(2.07)	(2.01)	(2.13)
LBM	-0.002	-0.002*	-0.005***	-0.005**	-0.007***	-0.006***
	(-1.49)	(-1.79)	(-2.66)	(-2.44)	(-2.95)	(-2.70)
TURN	-0.004	-0.001	-0.007	-0.005	-0.014	-0.011
	(-0.77)	(-0.19)	(-0.69)	(-0.53)	(-1.27)	(-0.99)
IVOL	0.511***	0.448***	0.744***	0.653***	0.860***	0.774***
	(6.85)	(6.35)	(6.05)	(5.80)	(5.38)	(5.39)
MOM	-0.003	-0.003	-0.006	-0.007	-0.007	-0.007
	(-1.12)	(-1.26)	(-1.25)	(-1.62)	(-1.25)	(-1.25)
RET1	-0.004	-0.001	-0.003	0.004	0.003	0.016
	(-0.55)	(-0.13)	(-0.24)	(0.41)	(0.20)	(1.27)
RET1D	-0.016	-0.025	-0.068*	-0.044	-0.044	-0.050
	(-0.59)	(-1.36)	(-1.83)	(-1.54)	(-1.27)	(-1.60)
ATT	0.002***	0.002***	0.003***	0.003***	0.002**	0.003***
	(3.62)	(4.47)	(2.83)	(3.50)	(2.12)	(2.65)
PRIOR	-0.001	-0.001	0.001	0.001	0.001	-0.000
	(-0.82)	(-1.07)	(0.50)	(0.32)	(0.32)	(-0.05)
Follow_Oppbuy	0.002*	0.002**	0.003***	0.003***	0.003**	0.003**
	(1.91)	(2.21)	(2.69)	(2.83)	(2.36)	(2.11)
Constant	-0.019***	-0.015**	-0.025***	-0.021**	-0.026**	-0.026**
	(-3.15)	(-2.55)	(-2.75)	(-2.23)	(-2.34)	(-2.23)
Day FE	No	Yes	No	Yes	No	Yes
Observations	19,917	19,801	19,900	19,784	19,895	19,780
R-squared	0.017	0.271	0.020	0.255	0.020	0.246

Table A7: Granger-type Causality Test

This table runs the Granger-type causality test by regressing retail order imbalance of stock i in week (oibvol) t on the 1-week lagged insider trading dummies (l_buy, l_opp_buy, l_rou_buy), as well as regressing insider trading dummies of stock i in week t (Buy, Opp_Buy, Rou_Buy) on the 1-week lagged retail order imbalance (l_oibvol), both in the insider-trading event window. We construct 1-week lagged insider trading dummy variables as a lagged insider buy dummy (l_buy), a lagged opportunistic buy dummy (l_opp_buy), a lagged opportunistic sell dummy (l_opp_sell), a lagged routine buy dummy (l_rou_buy), and a lagged routine sell dummy (l_rou_sell). The dummies equal one if the stock in week *t-1* has such an insider trade. We control for 1-week lagged dummies (l_prior_ins, l_prior_opp, l_prior_rou) indicating insider, opportunistic insider, and routine insider trades in week *t-2*. We include lagged firm size (l_lsize), lagged book-to-market ratio (l_lbm), lagged turnover (l_lturn), lagged idiosyncratic volatility (l_ivol), lagged momentum (l_mom), lagged short-term reversal (l_ret1), lagged prior week return (l_ret1w), lagged investor attention (l_att) as well as lagged retail investor attention (l_asvi) as control variables. The sample period is from January 2010 to December 2018. We use Fama-MacBeth regressions with Newey-West 5 lags adjusted. *p<0.1; **p<0.05, ***p<0.01.

Variable	(1) oibvol	(2) oibvol	(3) oibvol	(4) Buy	(5) Opp_Buy	(6) Rou_Buy
l_oibvol	0.213***	-0.043	0.213***	-0.012	-0.003	-0.000
	(12.20)	(-0.17)	(13.15)	(-0.85)	(-1.15)	(-0.45)
l_buy	0.073***			0.664***		
	(3.60)			(53.64)		
l_opp_buy		0.148***			0.623***	
		(3.01)			(28.24)	
l_rou_buy			-0.014			0.467***
			(-0.42)			(15.63)
l_lsize	0.017***	-0.018	0.014**	-0.025***	-0.008***	-0.001***
	(2.82)	(-0.57)	(2.30)	(-4.55)	(-7.78)	(-4.92)
l_lbm	-0.007	-0.022**	-0.020**	0.046***	0.008***	0.001
	(-0.63)	(-2.42)	(-2.42)	(5.69)	(5.33)	(0.52)
l_turn	0.073*	0.522	0.075**	-0.084***	-0.018**	-0.009**
	(1.67)	(1.35)	(2.19)	(-2.72)	(-2.56)	(-2.48)
l_ivol	3.972***	-25.471	3.527***	2.138***	0.223	-0.057
	(4.09)	(-0.93)	(3.56)	(3.95)	(1.21)	(-1.08)
l_mom	0.006	0.321	-0.027*	-0.068***	-0.008	0.006
	(0.33)	(1.02)	(-1.71)	(-4.72)	(-1.21)	(1.30)
l_ret1	0.004	-1.749	-0.024	-0.215***	-0.034***	-0.011
	(0.06)	(-1.07)	(-0.40)	(-7.37)	(-3.23)	(-1.42)
l_ret1w	-0.417	-7.736	-0.652	-1.145***	-0.205*	0.015
	(-0.89)	(-1.04)	(-1.33)	(-4.05)	(-1.83)	(0.19)
l_att	-0.000	-0.079	0.011**	0.001	0.001	-0.001***
	(-0.00)	(-0.93)	(2.26)	(0.31)	(0.74)	(-3.22)
l_asvi	0.001	0.152	0.008	-0.006	-0.000	0.000
	(0.15)	(1.05)	(1.29)	(-1.12)	(-0.22)	(0.88)
l_prior_ins	0.011	-0.117	0.013	-0.041***	-0.019***	-0.005***
	(0.82)	(-0.93)	(0.87)	(-3.68)	(-10.33)	(-2.92)
l_prior_opp		-0.103			0.018***	
		(-1.07)			(3.97)	
l_prior_rou			0.001			0.024***
			(0.04)			(5.31)
Constant	-0.447***	0.286	-0.417***	0.540***	0.155***	0.029***
	(-4.62)	(0.43)	(-4.40)	(6.74)	(10.98)	(7.76)
Observations	90,753	90,753	90,753	90,756	90,756	90,756
R-squared	0.190	0.195	0.191	0.471	0.382	0.472
Number of groups	456	456	456	456	456	456

Table A8: Cumulative Market-adjusted Returns on Stocks Traded by Retail Investors Following Insider Trading: Sub-sample Tests

This table reports the effect of retail investors following opportunistic insider purchases on market-adjusted returns for stocks with different levels of characteristics. We focus on firm book-to-market ratio (Panel A), prior month return (Panel B), Google ASVI (Panel C), institutional ownership (Panel D) as well as earnings surprise SUE (Panel E). In each panel we further separate the sample stocks into Follow portfolio and Not-Follow portfolio, based on whether retail investors follow insiders as defined in Table 1. In each panel, we categorize the sample of stocks into three levels of stock characteristics. For each level, we compute the difference in the cumulative market-adjusted returns between Follow portfolio and Not-Follow portfolio, up to 24 weeks. We use CRSP daily value-weighted market returns to calculate the average weekly market return, and subtract it from weekly stock return to get the weekly market-adjusted return. Standard errors are clustered at the week level. The returns are shown in percent. *p<0.1; **p<0.05, ***p<0.01.

Panel A: Sort by Book-to-market Ratio

Classification			Time Periods		
			Week 1 – Week 4	Week 1 – Week 12	Week 1 – Week 24
Low	Follow –	Mean	0.32***	0.04	-0.03
	Not-Follow	t-stat	(2.60)	(0.20)	(-0.11)
Mid	Follow –	Mean	0.13**	0.25**	0.27*
	Not-Follow	t-stat	(1.96)	(2.02)	(1.67)
High	Follow –	Mean	0.09	0.31	0.37
	Not-Follow	t-stat	(0.80)	(1.55)	(1.31)
High – Low	Diff. in Diff.	Mean	0.23	0.27	0.40
		t-stat	(-1.41)	(0.93)	(0.98)

Panel B: Sort by Prior Month Return

Classification			Time Periods		
			Week 1 – Week 4	Week 1 – Week 12	Week 1 – Week 24
Low	Follow –	Mean	0.26**	0.43**	0.70**
	Not-Follow	t-stat	(2.37)	(2.13)	(2.45)
Mid	Follow –	Mean	0.14*	0.20	0.11
	Not-Follow	t-stat	(1.71)	(1.35)	(0.56)
High	Follow –	Mean	0.17*	0.36*	0.01
	Not-Follow	t-stat	(1.77)	(1.73)	(0.04)
High – Low	Diff. in Diff.	Mean	-0.09	-0.08	-0.69*
		t-stat	(-0.60)	(-0.27)	(-1.73)

Table A8 (Cont.): Cumulative Market-adjusted Returns on Stocks Traded by Retail Investors Following Insider Trading: Sub-sample Tests

Panel C: Sort by Google ASVI

Classification			Time Periods		
			Week 1 – Week 4	Week 1 – Week 12	Week 1 – Week 24
Low	Follow –	Mean	0.07	0.36	0.60*
	Not-Follow	t-stat	(0.53)	(1.48)	(1.85)
Mid	Follow –	Mean	0.29**	0.66***	0.61*
	Not-Follow	t-stat	(2.20)	(2.63)	(1.93)
High	Follow –	Mean	0.23*	0.52**	0.36
	Not-Follow	t-stat	(1.75)	(2.28)	(1.08)
High – Low	Diff. in Diff.	Mean	0.16	0.16	-0.24
		t-stat	(0.87)	(0.47)	(-0.52)

Panel D: Sort by Institutional Ownership

Classification			Time Periods		
			Week 1 – Week 4	Week 1 – Week 12	Week 1 – Week 24
Low	Follow –	Mean	0.15	0.28	0.27
	Not-Follow	t-stat	(1.46)	(1.63)	(1.08)
Mid	Follow –	Mean	0.18**	0.14	0.09
	Not-Follow	t-stat	(2.36)	(0.97)	(0.41)
High	Follow –	Mean	0.13*	0.23*	0.24
	Not-Follow	t-stat	(1.76)	(1.76)	(1.43)
High – Low	Diff. in Diff.	Mean	-0.02	-0.05	0.02
		t-stat	(-0.14)	(-0.22)	(-0.07)

Panel E: Sort by Earnings Surprise (SUE)

Classification			Time Periods		
			Week 1 – Week 4	Week 1 – Week 12	Week 1 – Week 24
Negative SUE	Follow –	Mean	0.18**	0.30*	0.08
	Not-Follow	t-stat	(1.97)	(1.78)	(0.37)
No SUE	Follow –	Mean	0.12*	0.15	0.20
	Not-Follow	t-stat	(1.80)	(1.20)	(1.26)
Positive SUE	Follow –	Mean	0.23**	0.40*	0.42
	Not-Follow	t-stat	(2.33)	(1.84)	(1.41)
Positive – Negative	Diff. in Diff.	Mean	0.04	0.10	0.34
		t-stat	(0.35)	(0.38)	(0.93)