Retail Investor Trading and Market Reactions to Earnings Announcements*

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Abstract

We use trade-level data and exploit retail brokerage outages to examine how retail investors affect the pricing of public earnings information. Retail trading is associated with stronger price responses to earnings news during the earnings announcement (EA) window and greater short-term post-earnings announcement drift (PEAD). Prior to earnings announcements, retail activity is associated with less informative returns. Retail buy-sell imbalance is not associated with EA returns or PEAD. We discuss several potential theories of retail trade in light of our evidence. Overall, retail investors appear to facilitate the impounding of public earnings signals but dampen the revelation of private earnings-predictive signals in pre-announcement returns. Results are consistent with a theory of retail traders dynamically providing liquidity to other investors who choose how intensely to obtain and trade on earnings news.

Keywords: Retail investors; Earnings announcements; Stock returns; ERC; PEAD
JEL codes: G11; G14; G51; M41

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1 Introduction

Stock prices often fail to reflect any and all public information, despite the intuitive appeal of semi-strong market efficiency. Retail investors, as relatively unsophisticated capital market participants, are often viewed as the source of trades that impound noise into prices and slow or stop prices from reacting efficiently to information (see, e.g., the evidence reviewed by Barber and Odean, 2013). However, retail traders over the last several years have broadly gained access, via web-based technologies, to real-time public information as well as inexpensive means to trade on that information. Additionally, their trading activity can provide liquidity to other market participants who help impound informative signals into prices. There are several competing theories and narratives describing retail investors' activity in capital markets, ranging from views of retail traders as pure noise traders to considerations of retail traders as relatively informed. There are also intermediate narratives that describe retail investors as over- or under-reacting to some signals (e.g., due to overconfidence or (in)attention) while responding appropriately (i.e., rationally) to others.

In this study, we use novel retail trade indicators developed by Boehmer et al. (2021) to examine how retail trading affects stock market pricing of corporate information. Our efforts are aimed at providing evidence that can help distinguish between theories and narratives regarding retail investor activity. We focus specifically on how retail activity affects the pricing of earnings news in the days before the announcement, during the earnings announcement window, and in the weeks and months following the earnings announcement. To derive plausibly causal estimates of the effects of retail trade on the pricing of earnings news, we exploit data on outages at retail brokerages, which serve as random shocks to retail traders' ability and/or cost to trade (Barber et al., 2021; Eaton et al., 2022).

We proceed chronologically around the earnings announcement (EA), starting with the pre-EA period. Prior studies suggest that informed trading prior to announcements can impound information about earnings into price (e.g., Baruch et al., 2017), though biases such as optimism can make pre-announcement returns noisy and lead to reversals (Aboody et al., 2018; Trueman et al., 2003). On average, returns in the 10 days prior to an earnings announcement are strongly associated with the realized earnings surprise in our sample. Germane to our research questions, this positive association is significantly weaker when there is more retail activity during the pre-announcement window, suggesting that retail trade tends to reduce the amount of (predictive) earnings information in pre-announcement returns.

We find that stock returns are more responsive to earnings surprises when retail traders are more active in the stock. That is, earnings response coefficients (ERCs) are higher when there is more retail activity. We then turn to the predictability of post-earnings returns, which are often used to capture departures from semi-strong market efficiency (e.g., DellaVigna and Pollet, 2009; Even-Tov, 2017; Hirshleifer et al., 2009). We find that retail activity during the earnings announcement window is associated with greater post-EA drift (PEAD) in the direction of the earnings surprise in the week following the earnings announcement, consistent with retail traders contributing to PEAD. This initial evidence contrasts with the finding of Hirshleifer et al. (2008) that retail activity plays little role in driving PEAD. Notably, our samples cover vastly different periods (early 1993-1996 versus 2010-2021), and capture retail trade using different methodologies.

Of course, retail trading is endogenous in the earnings announcement setting because investors choose whether and how much to trade based on information about earnings, stock prices, other market participants, and features both observable and unobservable empirically. To identify a plausibly causal effect, we exploit retail brokerage outages whose timing is seemingly random relative to the timing and information content of firms' earnings announcements. These brokerage outages increase the trading frictions faced by retail traders and lead to less activity (Barber et al., 2021; Eaton et al., 2022). Exploiting the exogeneity of the brokerage outages, we show that retail frictions are associated with weaker price responses to earnings announcements and less short-term (one-week) PEAD.

The positive effect of retail trade on both ERCs and PEAD is inconsistent with several theories discussed in further detail below, but is consistent with two theories. In the first, retail traders are susceptible to noisy signals but trade on information such as earnings announcements (Bushee and Friedman, 2016). In the second, retail traders provide liquidity dynamically to other traders who can choose the intensity with which they acquire private signals (Banerjee and Breon-Drish, 2020), which can be interpreted as paying attention to public disclosures such as earnings announcements (Blankespoor et al., 2020). Additional analysis based on retail traders' buy-sell imbalance around earnings announcements supports the dynamic liquidity provision theory over the susceptible investor theory. Dynamic liquidity is further supported by stronger effects around positive earnings surprises than negative surprises, given lower costs of trading on positive rather than negative news. Our results are also robust to several alternative specifications and within various subsamples that align with the dynamic liquidity interpretation.

We discuss related literature and theories in Sections 2 and 5 but note here two extant studies that are particularly close to ours. First, Hirshleifer et al. (2008) use the 1991-1996 discount brokerage data (see also Barber and Odean, 2000) to examine whether individual investors' trades help explain PEAD.[1] Hirshleifer et al. (2008) conclude that PEAD is not caused by individual investors. Rather, individual investors are net buyers after both positive and negative earnings surprises, and their net trades are not associated with PEAD. Despite the similarities, our study differs in several important respects from Hirshleifer et al. (2008). First, our research question is substantively different. We focus on how retail investor activity affects market responses to earnings announcements during the announcement window as well as before and after. Second, retail trading behavior is plausibly different in our 2010-2021 sample compared to their 1991-1996 sample, due to factors including changes in information availability, processing costs and trading technology. Third, retail brokerages experienced multiple outages during our sample frame that made it more difficult for retail investors to

[1] Bartov et al. (2000) show that institutional holdings are negatively associated with PEAD, but note that institutional holdings are an imperfect proxy for investor sophistication. Their results do not speak directly to the question of retail traders' potential effects on the pricing of earnings news.

trade. We exploit these outages as exogenous increases to retail frictions that allow us to better identify the effects of retail trading per se. The biggest inferential difference from Hirshleifer et al. (2008) is that our results suggest that retail investors on average help impound public information around earnings announcements, while potentially reducing the degree to which pre-announcement returns reflect earnings information. This contrasts with their finding of individual investors engaging in attention-based purchasing and simply not contributing to PEAD.

Second, the concurrent study by Michels (2021) exploits data on Robinhood holdings to examine retail activity around earnings announcements.[2] However, Michels (2021) focuses on changes in holdings around and *following* earnings announcements, and differential effects of positive versus negative earnings surprises with a focus on investor attention. In contrast, we exploit plausibly exogenous outages and the Boehmer et al. (2021) measure of retail trade to develop our inferences and show that they generalize beyond Robinhood holdings per se.

Our study contributes to our understanding of retail traders and market reactions to earnings news. We focus on earnings announcements because they are salient, pre-scheduled public information releases. Overall, our results provide the most consistent support for a narrative in which retail traders provide liquidity allowing reactions to and incorporation of public information but also can impound noise into prices. Our pattern of results tends not to support simpler narratives in which retail traders are either always (on average) impounding noise into returns or always pushing prices towards efficient incorporation of public information. Notably, this suggests a conceptualization of retail traders that is dynamic and potentially context-dependent, relying on the availability of public information, transaction costs, and other traders' responses to retail trade.

The next section provides background and institutional detail regarding retail trade. Section 3 describes the data, and Section 4 presents our main results. Section 5 discusses several prominent theories and narratives for how retail trade would affect the pricing of

[2] A previous version of our paper also used Robinhood holdings data.

earnings information, with attention to which are supported or rejected by our findings in Section 4. Section 6 provides additional tests that further distinguish between theories, as well as robustness checks. Section 7 concludes.

2 Background and related literature

Retail trading refers to trading by households and non-professional investors, in contrast to trading by professionals including institutional investors, hedge funds, financial institutions, and asset managers. Prior studies (reviewed in Barber and Odean (2013) and Blankespoor et al. (2020)) have found significant evidence of retail investors underperforming relative to low-cost benchmarks, buying and selling at disadvantageous times, under-diversifying, and being subject to behavioral factors such as the disposition effect.

Several studies have empirically examined the role of retail traders in capital markets. Barber and Odean (2000) use a now-popular data set from a large discount brokerage in the early to mid 1990s to show that households make poorly-performing stock trades on average. Grinblatt and Keloharju (2000), using data on trades made by Finnish households, reach a similar conclusion. Given the sparse access to data on individuals' portfolios and trades, many researchers have used low-latency Trade and Quote (TAQ) data to study the performance of retail investors. Prior studies interpreted small trades (less than $5,000) as coming from retail rather than institutional investors (e.g., Hvidkjaer, 2008).

Intermediaries are important conduits of retail trade. Retail investors access capital markets information and trade through securities brokers and investment management firms, who historically have generated revenue through trading commissions and fees on assets under management. The recent emergence of technology firms in the financial space (fintech) has disrupted these revenue streams. Robinhood's no-commission trading quickly attracted a large number of retail investors, and was followed in 2019 by elimination of trading commissions at other large brokerages popular among retail traders (Osterland, 2019). As of April

1, 2021, TD Ameritrade, E*Trade, Charles Schwab, Vanguard, Fidelity, Bank of America (Merrill Edge) and J.P. Morgan Chase (J.P. Morgan Self-Directed Investing) all offer zero-commission equity trading.[3]

Instead of commissions, retail brokerages now generate revenue through payment for order flow, margin lending to traders, lending of securities to short sellers, and net interest on investors' cash positions. Payment for order flow refers to the practice of wholesale market makers (e.g., Citadel Securities, Virtu Financial, and Two Sigma) offering rebates to retail brokerages for routing their order flow to the wholesaler for execution. Often, the orders are executed at prices that are fractions of a cent better than the National Best Bid and Offer (NBBO) available on public exchanges. Following Boehmer et al. (2021), we exploit these sub-penny price improvements observable in TAQ data as indicators of payment for order flow and thus retail trade.

Numerous channels, including brokerage platforms themselves, provide retail investors with information about earnings realizations, expectations, and interpretations both by professionals and peers (e.g., Farrell et al., 2020). Several retail brokerage houses provides push notifications about upcoming and recent earnings announcements (Moss, 2022), make it easy for users to listen to earnings calls, and incorporate data from multiple vendors and markets.[4] Because public information and context has become easily accessible, retail investors may now contribute to the impounding of earnings information into price, even if they hindered it in the past (i.e., in studies using earlier samples).

Interestingly, retail brokerages occasionally experience outages, which can limit their users' ability to trade. Outages can be due to technical problems with the broker's system or periods of heightened market stress (e.g., around March 2-3, 2020). Eaton et al. (2022) document retail broker outages using complaints histories available from downdetector.com.

[3]See Nerdwallet's list at `https://www.nerdwallet.com/best/investing/free-stock-trading`.

[4]Robinhood provides the following information about their data sources: "Certain fundamental, market data, and other information is provided by FactSet Research Systems, Inc. ..., by Xignite (xignite.com), ICE Data Services, and/or other third party providers." Accessed at `https://cdn.robinhood.com/assets/robinhood/legal/RHF\%20Product\%20Features\%20Disclosures.pdf` on May 13, 2021.

We use their outage and complaints data as a source of variation exogenous to other factors influencing retail trading around earnings announcements (particularly after controlling for market stress as reflected in volume). The conditionally random nature of outages allows us to attribute changes in market pricing of earnings information around outages to the effects of (a reduction in) retail trade. In particular, the outages appear to be randomly timed relative to corporate earnings news, as we show below.

Although individual retail investors tend to be small, their impact on markets can be large. As of mid-2020, retail trading accounted for roughly 20% of market activity (Winck, 2020), partly facilitated by low-cost platforms such as Robinhood. In individual stocks, retail flows can cause large price movements. As examples, note recent episodes involving volatility in Gamestop, AMC Entertainment Holdings, Blackberry and Nokia, discussed in Lyócsa et al. (2021). Boehmer et al. (2021) find that retail order flow predicts returns over the subsequent week, though Eaton et al. (2022) find no evidence of Robinhood holdings predicting stock returns.

In our main analysis, we focus on how retail trade affects our three empirical outcomes of interest. The first outcome of interest is the degree to which earnings information is incorporated into returns before the earnings announcement (EIPAR: earnings information in pre-announcement returns). EIPAR can be the result of some traders having private information or processes that allow them to predict the earnings surprise. The second is the earnings response coefficient (ERC), which captures the sensitivity of returns during the announcement window to the news contained in the earnings announcement, captured by the earnings surprise. The third is post-earnings announcement drift (PEAD), which are systematic trends in returns associated with earnings surprises following earnings announcements.

3 Sample and variables

3.1 Earnings announcements

Our sample period runs from Jan 2010 to Dec 2021. We focus on the post 2010 period since the practice of internalization and offering price improvements to retail investors was generally adopted by brokerage firms and wholesalers by 2010 (Boehmer et al., 2021). Table 1 describes our sample selection process. The unit of analysis is the quarterly earnings announcement for U.S. common stocks with data at the intersection of TAQ, CRSP, Compustat, and IBES. Starting from announcements available in Compustat and CRSP, we drop announcements (i.e., firm-quarters) that are missing controls, cannot be linked to IBES, missing returns or trading volume on a particular announcement day (77,550), or are not traded on NYSE/NASDAQ/AMEX (38,974).[5] This leaves a sample of 4,218 unique firms with nearly 100,000 quarterly earnings announcements in our sample time frame. Variable definitions are provided in Appendix B.

Recent studies show that a great number of earnings announcements occur outside of market hours (e.g., Bochkay et al., 2020). To account for earnings released after markets close, we collect earnings announcement timestamp data from IBES, and adjust the earnings announcement date to one trading day after for earnings released after 4 pm Eastern Time.[6]

3.2 Retail trading

Our measure of retail trading follows Boehmer et al. (2021). We obtain transaction data from the daily TAQ database.[7] As a first step, we classify trades as retail buys (sells) in the TAQ data if they have exchange code D and the trade was executed at a price just below (above)

[5] We also drop observations where earnings are announced more than 100 days after the fiscal period end and those with very high or low estimated earnings persistence ($abs(EPersistence) > 100$).

[6] For after-hour (pre-market) announcements, our earnings announcement window return, i.e., $BHAR[0, 1]$ based on close-to-close returns, captures the post-market (pre-open) market activities.

[7] We clean the daily TAQ data following steps in Holden and Jacobsen (2014).

a round penny.[8] Then, based on the identified retail trades, we calculate retail volume as

$$\text{Retail Volume}_{i,t} = \text{Retail Buys}_{i,t} + \text{Retail Sales}_{i,t} \tag{1}$$

where $Retail\ Buys_{i,t}$ and $Retail\ Sales_{i,t}$ are individual-initiated buying and selling volumes in dollars during interval t for stock i, respectively.[9] In our analyses, t is the one-day window (on the adjusted earnings announcement day). To address skewness, we take the natural log of $Retail\ Volume$ when using it as a measure of retail trade. Nonretail trade is defined as total market volume minus $Retail\ Volume$, and we use the log of nonretail volume in our tests to help alleviate concerns that our measure of retail volume is merely serving as a proxy for aggregate trading.

Figure 1 shows quarterly log market volume over our sample period (vertical bars) separately for small and big firms, based on a market capitalization median split. Unsurprisingly, big firms tend to have larger volume. Average quarterly % Retail Volume for each subset of firms is also displayed in Figure 1 (solid and dashed curves). Retail trade is more prominent in small firms, hovering around 12% for much of the sample period, relative to values around 4-6% for big firms. Overall, except for a rise in % Retail Volume for small firms during 2013, there do not seem to be significant secular patterns either for total market volume or % Retail Volume.

Figure 2 shows patterns of retail and nonretail volume for the 60 days around earnings announcements. As in Figure 1, we present averages for small and big firms (by market capitalization) separately. Similar to Figure 1, average nonretail volume is larger than retail

[8]Trades executed with the tenth-of-a-cent digit between 0 and 4 (6 and 9) are classified as retail sells (buys), as they reflect price improvement to the seller (buyer) relative to round penny prices. Most market orders initiated by retail investors are either internalized by brokers or sent to wholesalers. These orders do not take place on registered exchanges and will be recorded in TAQ with exchange code D. Orders routed to wholesalers are typically filled with prices that are slightly better than the national best bid and offer, and these price improvements are usually less than a penny. Note that institutional investors are prohibited from receiving sub-penny price improvements by Reg NMS.

[9]Retail trades identified based on Boehmer et al. (2021) capture marketable retail orders. Kelley and Tetlock (2013) document the aggressive nature of retail trade using data from dozens of retail brokerages. In their 2003-2007 sample, retail investors mainly submit market orders to fulfill their trading needs (i.e., the number of retail market orders exceeds the number of nonmarketable limit orders by more than 35%).

volume in both subsamples, and for each day around the earnings announcement. Both small and large firms experience spikes in both retail and nonretail volume that begin a couple days before the earnings announcement and dissipate after. While the magnitudes (i.e., levels) differ across types of trade and firm size, the time series patterns are generally similar.

3.3 Brokerage outages

Retail brokerage platform outages data comes from Downdetector.com, as compiled and provided by the generous authors of Eaton et al. (2022). Downdetector.com captures user complaints reporting outages at websites in general. Eaton et al. (2022) collected outage complaints data for several retail brokerages including Charles Schwab, E-trade, Fidelity, TD Ameritrade, and Robinhood measured at 5 minutes intervals. We remove outages that were plausibly misreported by removing those with less than 200 outage complaints (Eaton et al., 2022). We define *Outage* as an earnings announcement level indicator that takes the value of one if the aggregate outage complaints during the firm's adjusted earnings announcement date are in the top quintile (at least 803) for daily complaints in the time frame covered by Eaton et al. (2022). To alleviate the concern that outages are driven by market-wide factors, we remove outages experienced by all brokers during the same 5-min interval as suggested in Eaton et al. (2022).[10] We control for total market volume in all analyses to avoid spurious inferences due to brokerage outages driven specifically by high-volume days.

[10] While Eaton et al. (2022) focus on the effect of different retail investor clienteles on stock market liquidity, our focus is on the aggregate retail trading and how it affects the pricing of earnings news. Thus, we do not conduct analyses separately for traditional brokers and Robinhood. We direct interested readers to Eaton et al. (2022) for analyses exploring broker-specific features.

3.4 Market reactions to earnings announcements and controls

For our analyses of market reactions to earnings announcements, we measure earnings surprise, SUE, following Livnat and Mendenhall (2006) as:

$$\mathrm{SUE}_{i,t} = \frac{\mathrm{X}_{i,t} - \mathbb{E}[\mathrm{X}_{i,t}]}{\mathrm{P}_{i,t}}$$

where i denotes firm, t denotes quarter, $X_{i,t}$ are IBES reported actual earnings, $\mathbb{E}[X_{i,t}]$ are expected earnings, taken as the latest median forecast from the IBES summary file, and $P_{i,t}$ is the share price at the end of quarter t.[11]

Daily excess returns are calculated each day as firm-specific returns net of returns on a size and book-to-market matched portfolio.[12] Earnings announcement returns used for earnings response coefficient (ERC) tests are calculated as cumulative excess returns from the day of the earnings announcement through the day after (two-day window). Additionally, we examine the pre-earnings announcement window from 10 days before the earnings announcement to the day before for pre-earnings returns, as well as several post-earnings announcement windows from 2 days after the earnings announcement to 5 days, 22 days, 45 days, and the subsequent earnings announcement to capture post-earnings returns over the week, month, 2 months, and quarter following the earnings announcement, respectively. As in prior studies (e.g., DellaVigna and Pollet, 2009), we use 11 SUE quantiles (5 negative quintiles, 5 positive quintiles, and a no-surprise quintile) based on calendar-quarter sorts rather than raw values when SUE is an independent variable.[13]

We use the following variables as controls, following prior literature (e.g., Hirshleifer et al., 2009): compound excess returns from ten to one days before the earnings announcement

[11] Several variable definitions are similar to those in Andrei et al. (2021). The earnings surprise calculation follows WRDS guidance described in Dai (2020).

[12] We use 25 matching portfolios based on the intersections of 5 portfolios formed on market capitalization and 5 portfolios formed on book-to-market (i.e., independent sorts), similar to `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/tw_5_ports.html`. Portfolios are formed annually and matched to firms on June 30 based on firm size (market capitalization) and book-to-market.

[13] Our results are robust to using raw SUE (untabulated).

(PreRet); the market value of equity on the day of the earnings announcement (Size); the ratio of book value of equity to the market value of equity at the end of the quarter for which earnings are announced (Book-to-Market); earnings persistence based on estimated quarter-to-quarter autocorrelation (EPersistence); institutional ownership as a fraction of total shares outstanding at the end of the quarter for which the earnings are announced (IO); earnings volatility (EVOL); the reporting lag measured as the number of days from quarter end to the earnings announcement (ERepLag); analyst following defined as the number of analysts making quarterly earnings forecasts according to the IBES summary file (# Estimates); average monthly share turnover over the preceding 12 months (TURN); an indicator variable for negative earnings (Loss); the number of other firms announcing earnings on the same day (# Announcements); year-quarter indicators; and day-of-week indicators.[14]

3.5 Descriptive statistics and correlations

Descriptive statistics are provided in Table 2. Raw earnings surprises are on average near zero, but with wide dispersion, with an especially long left tail. Our quantile-based SUE measure addresses the dispersion and ranges from 1 to 11. Values of 1-5 are the negative quintiles; 6 represents no surprise, and 7-11 capture the positive quintiles. Average abnormal returns over the various windows examined are also close zero. In contrast, the average log value of retail volume during announcement window is around 14, which does not substantially deviate from the value prior to the earnings announcement. Most earnings announcements are made on days with no complaints about retail brokerage outages on Downdetector.com.

Table 3 shows raw pairwise correlations. The earnings surprise quantile, SUE, is positively and significantly correlated with abnormal returns during the announcement window and most of the post-announcement window returns. SUE and announcement-window returns are also both negatively associated with the log of volume attributable to retail investors and

[14]When our coefficient of interest is on an interaction between our retail measures and SUE, we also interact all control variables (excluding fixed effects) with SUE.

non-retail investors (i.e., trades that are not classified as retail buys or sells by the algorithm). The log of retail volume is also significantly correlated with the announcement-firm controls, consistent with there being several plausible factors contributing to the trading mix around earnings announcements. In all of the tests on which we base inferences, we include controls for firm, market, and announcement characteristics to mitigate the potential to estimate confounded relations between retail trade and our returns-based dependent variables.

4 Results

We proceed chronologically around the earnings announcement, beginning with results focusing on retail trade prior to the earnings announcement. These analyses help demonstrate whether retail trade facilitates or impedes the revelation of upcoming earnings information in price (EIPAR). We next present tests relating retail trading activity to price responses to earnings surprises, i.e., ERC's. We then examine the association between retail trade during the earnings announcement window and post-earnings returns, focusing on potential drift and reversal. Given the endogenous nature of trading decisions that inherently depend on available information and incentives, we next introduce brokerage outages as a plausible shock to retail trade. We show that outages lead to less retail trade, then examine how outages during earnings announcement windows affect ERC's and PEAD. After interpreting our results in light of various theories and narratives around retail trade in Section 5, we present additional analyses in Section 6.

4.1 Earnings information in pre-announcement returns (EIPAR)

In this section, we consider how retail trade affects the degree to which earnings information is reflected in prices prior to the earnings announcement, based on how well pre-EA returns predict the earnings surprise. Specifically, to examine potential effects of retail trade on

EIPAR, we estimate the following regression

$$\begin{aligned} \text{SUE}_{it} = &\beta_0 + \beta_1 \text{PreRetail}_{it} + \beta_2 \text{PreRet}_{it} + \beta_3 \text{PreRetail}_{it} \times \text{PreRet}_{it} \\ &+ \sum \beta_k X_{k,it} + \epsilon_{it} \end{aligned} \tag{2}$$

where PreRet is the compound abnormal return (relative to the size and book-to-market matched portfolio) for days -10 through -1 relative to the EA day 0. Similarly, PreRetail is retail volume scaled by total volume for trading days -10 through -1 prior to the EA date. Estimates of equation (2) test whether returns in the days prior to an earnings announcement help predict the earnings surprise, SUE, and whether retail trading during those days affects the predictive relation.

Results for the main coefficients of interest from estimating equation (2) are shown in Table 4. The first column presents estimates with fixed effects but without controls. We find a positive and significant coefficient on PreRet ($\beta = 0.198$, $p < 0.01$), implying that pre-EA returns have predictive value for the earnings surprise. The coefficient of interest on PreRetail $\times$ PreRet is negative and significant ($\beta = -0.151$, $p < 0.01$), consistent with retail activity reducing the degree to which pre-EA returns help predict the earnings surprise. We interpret this as a negative association between retail trade and EIPAR. NonRetail trade prior to the earnings announcement, in contrast, is associated with higher EIPAR. The coefficient estimates are substantially similar in column 2, where the addition of controls for earnings persistence and volatility help alleviate concerns that the results are confounded by retail traders selecting to trade more in advance of harder-to-predict earnings.

4.2 Earnings announcement returns and retail activity

Turning to the association between retail trading and ERC's. We estimate the following regression at the firm-quarter level:

$$\begin{aligned}\text{BHAR}[0,1]_{it} = \beta_0 + \beta_1\text{SUE}_{it} + \beta_2\text{Log(Retail)}_{it} + \beta_3\text{SUE}_{it} \times \text{Log(Retail)}_{it} \\ + \sum \beta_k \text{X}_{k,it} + \sum \beta_k \text{SUE}_{it} \times \text{X}_{k,it} + \epsilon_{it},\end{aligned} \tag{3}$$

where the dependent variable is the announcement-window abnormal return, Log(Retail)_{it} is a measure of retail trading activity from TAQ, and X_{it} represents a set of controls described in Section 3.4. β_1 captures the average ERC. The coefficient of interest is β_3 on SUE $\times\text{Log(Retail)}_{it}$, which captures the incremental effects of retail trade on the ERC. All variables are standardized to be mean-zero and unit-variance to facilitate the interpretation of the non-interacted main effects and economic magnitudes of interactions.

Coefficient estimates are presented in Table 5. Column 1 presents a specification without control variables besides year-quarter, day-of-week, and firm fixed effects. In this specification, the coefficient on SUE is 0.210 ($p < 0.01$), implying a positive and both economically and statistically significant ERC. The coefficient on SUE $\times\text{Log(Retail)}_{it}$ is positive and significant ($\beta = 0.130$, $p < 0.01$). This implies a positive relation between retail trade activity and ERC's.[15]

Column 2 shows results for a specification including controls and their effects on ERC's as captured by interactions between each control and SUE. We view this specification as more reliable as it allows for identification of the effect of retail trade on ERC's separate from potential confounds (e.g., size, analyst coverage, and prior turnover). In this specification, the estimated average ERC is slightly lower, at 0.170 ($p < 0.01$). Of primary interest the coefficient on SUE $\times$ log(Retail) remains positive and significant ($\beta = 0.092$, $p < 0.01$).

Before continuing, we comment briefly on economic magnitudes. Focusing on the estimate

[15] Of potential interest, the EA-window association between retail trade and abnormal returns is negative. However, this does not reflect a reaction to information per se, and is thus not our focus.

in column 2 of Table 5, and recalling that variables are standardized to mean-zero and unit-variance, our estimate implies that a one standard deviation change in Log(Retail) is associated with an ERC that is higher by around 0.09. This is over 50% of the average ERC of 0.170, which is economically meaningful.

4.3 Post-earnings announcement returns and retail activity

This section presents tests of the association between retail trade during the earnings announcement window and post-earnings returns, focusing on potential drift. These tests are based on estimates of equation (3) with earnings announcement window returns (BHAR[0,1]) replaced by post-earnings returns (BHAR[2,5], BHAR[2,22], BHAR[2,45], and BHAR[2,next]) as the dependent variable.

Results are presented in Table 6. For comparison, column 1 shows the coefficients estimated using BHAR[0,1] as the dependent variable, as in column 2 of Table 5. Columns 2 through 5 present estimates for post-earnings windows over one week, one month, two months, and through the next earnings announcement, respectively.

The coefficients on SUE in columns 2 through 5 are positive but not *consistently* significantly different from zero at conventional levels ($p < 0.01$ in columns 2 and 3 but $p > 0.10$ in columns 4, and 5). This inconsistent evidence contrasts with prior studies finding positive post-earnings announcement drift (e.g., Bernard and Thomas, 1990), particularly through the subsequent earnings announcement, but comports with recent evidence of the attenuation of the PEAD anomaly (e.g., Chordia et al., 2014).

Our coefficients of interest, on the SUE $\times$Log(Retail) interaction, are consistently positive, though among the PEAD regressions only the coefficient in column 2 for BHAR[2,5] is significant at conventional levels ($p < 0.01$). This suggests that EA window retail trade is associated with post-EA return drift in the direction of the earnings surprise through, roughly, the week following the earnings announcement.[16] Overall, retail trading appears to

[16]Interestingly, our inferences for retail trade from Table 6 also hold for nonretail trade, suggesting that

facilitate a modest degree of short-term PEAD.

4.4 Earnings announcement returns and retail frictions from platform outages

Our results suggest that retail traders help incorporate publicly available earnings information into stock prices during the EA window while also creating space for PEAD or otherwise trading in a manner that facilitates short-term continuation. However, retail trading is endogenous to the earnings response setting, as investors, including retail investors, clearly choose whether and how much to trade based on information about earnings, stock prices, additional signals, and other features both observable and unobservable to researchers. Due to this endogeneity, we interpret our results above as indicative of interesting associations, rather than a causal effect of retail trading on price responses to earnings information.

To identify a plausibly causal effect, we exploit seemingly randomly timed outages experienced by retail brokerages. These outages made it more difficult (nigh impossible) to trade on various platforms. Thus, they capture variation in retail trading frictions that are exogenous to a given firm's earnings announcement and its information content. To verify the negative effect of outages on retail volume, we estimate the following regression:

$$\text{Log(Retail)}_{it} = \beta_0 + \beta_1 \text{Frictions}_t + \sum \beta_k \text{X}_{it} + \epsilon_{it} \tag{4}$$

where Log(Retail)_{it} is the retail trading volume during 5-minute interval t for stock i. Frictions_t represents either Outage (an indicator for top-quintile complaints) or # Complaints (aggregate user complaints during a 5-min interval). We estimate equation (4) on a sample including 5-min intervals during outages, matched with intervals 1 trading day before and after for the same stock and time of the day. In these regressions, we do not focus on earnings announcements. Table A.1 presents our estimates of equation (4). We find that outages are negatively associated with retail volume, as expected, and in line with Barber

trade in general during the EA window slows the reaction to EA news.

et al. (2021) and Eaton et al. (2022).

We exploit the outages as shocks whose timing is random with respect to earnings announcements to provide more plausibly causal evidence on the effects of retail trading on market reactions to earnings information. We estimate specifications similar to (3), but focusing on the effects of retail broker outages as the main independent variable:

$$\text{BHAR[a,b]}_{it} = \beta_0 + \beta_1 \text{Outage}_t + \beta_3 \text{SUE}_{it} \times \text{Outage}_t + \sum \beta_k \text{X}_{k,it} + \sum \beta_k \text{SUE}_{it} \times \text{X}_{k,it} + \epsilon_{it} \tag{5}$$

where $Outage_t$ is an indicator variable for adjusted earnings-announcement dates featuring top-quintile brokerage outage complaints. As before, our ERC tests use BHAR[0,1] as the dependent variable. Our PEAD tests use BHAR[2,5] (1 week), BHAR[2,22] (1 month), BHAR[2,45] (2 months), and BHAR[2,next] (1 quarter). We include the same fixed effects, controls, and controls interacted with SUE as in Table 6, as well as a control for Log(MktVol) and its interaction with SUE, given the potential for volume-related stress to jointly affect returns and the probabilities of brokerage outages. For our tests using brokerage outage complaint data, we limit the sample to the January 2019 - June 2021 period covered by the Eaton et al. (2022) outage data.

Results of estimating equation (5) are shown in Table 7. In column 1, the ERC remains positive and similar in magnitude to prior estimates ($\beta = 0.152$, $p < 0.01$). As in Table 6, there is evidence of a post-earnings announcement drift in the direction of the earnings surprise only for the week following the earnings announcement ($\beta = 0.084$, $p < 0.01$ in column 2). Coefficients on SUE in columns 3, 4, and 5 are all less than 0.01 and are insignificantly different from zero.

Turning to the coefficient of interest on Outage × SUE, its estimate of -0.0613 ($p < 0.05$) in column 1 implies that retail brokerage outages are associated with smaller ERCs. As outages serve as a negative shock to retail trade, this implies that our positive association between retail trade and ERCs is plausibly causal. Similarly, the coefficient on Outage ×

SUE columns 2 is negative and marginally significant ($\beta = 0.046$, $p < 0.10$), while coefficients on this interaction in columns 3-5 are smaller and statistically insignificant. This aligns with our estimated positive association between retail trade and one-week PEAD shown in Table 6, supporting our inference of a positive causal effect of retail trade on short-term PEAD.

5 Theories and narratives of retail trade in light of our results

Our analyses thus far suggest that retail trade is positively associated with ERCs and short-term PEAD, as well as greater noise prior to earnings announcements. Prior studies have developed several narratives and sets of related hypotheses relating to different ways in which retail traders might affect market prices and the information content of prices. We discuss several of these in this section in a reasonably comprehensive manner that captures broad categories reflected in the literature. Nonetheless, we acknowledge the likelihood of unintentional omissions. Our primary goal is to compare and assess competing theories in light of our evidence. The general pattern of our evidence is that retail trade is associated with lower EIPAR, higher ERC's and modestly higher near-term PEAD. Where appropriate, we also as suggest additional tests that may help further distinguish between or support relevant theories We operationalize these tests in the penultimate section of the paper.

5.1 Retail traders are no different

The most common models of capital markets typically assume investor homogeneity or, equivalently, that investors' effects on prices and returns can be summarized by a single representative investor. Even if investors are heterogeneous, their differences are idiosyncratic and wash out in the aggregate.[17] In these models, retail investors would have no effect on

[17] The homogeneous or representative investor model is consistent with but not equivalent to semi-strong market efficiency, which implies that prices should respond fully and completely to public information, regardless of the composition of traders. Investors can be homogeneous but still face frictions that cause prices to react slowly to information releases. The key is whether the departure from semi-strong efficiency is related to or driven by the composition of traders.

the pricing of corporate earnings. Under the *no difference* narrative, more retail activity would not be associated with EIPAR, ERCs, PEAD. Our findings are inconsistent with the narrative/theory that retail trade is not systematically different from non-retail trade.

5.2 Retail traders are noise traders

5.2.1 Static noise trade and liqudity provision

A common convenience assumption in capital market models is that there is a set of traders who trade for reasons orthogonal to the information about an asset's value, such as idiosyncratic liquidity shocks, misinterpretation of signals, or mood (e.g., Black, 1986). These traders, particularly in noisy rational expectations models (e.g., Hellwig, 1982; Grossman and Stiglitz, 1981; Verrecchia, 1982; Diamond and Verrecchia, 1981) exist in part to prevent stock prices from fully revealing informed traders' information. Mechanically, noise traders move price away from fundamentals, weakening the link between fundamental information and asset values, while providing liquidity that can motivate other market participants to acquire relevant information (e.g., Kyle, 1985). Noise traders can also have a negative effect on liquidity, by increasing market makers' expected inventory costs (e.g., Ho and Stoll, 1981) or imposing risk on market participants in general, leading to greater price protection (e.g., De Long et al., 1990).[18] Overall noise trade around public information releases tends to weaken the price response to the information or the degree to which returns reflect private anticipatory information prior to the EA. If retail trades are primarily noise as captured in single-period/static models, then we would expect greater retail activity to be associated with lower EIPAR, weaker ERCs, and plausibly greater PEAD as prices slowly incorporate earnings news. The pattern of our results does not support the static noise trade narrative and related theories.

Retail traders, while acting as noise traders who potentially generate uninformative price

[18] The evidence in Eaton et al. (2022) is consistent with some retail investors behaving as coordinated noise traders that market makers price protect against, while other retail investors are net liquidity providers.

pressure, can create liquidity that allows other traders to impound information. Increased liquidity and the exploitation of that liquidity by informed traders should be associated with prices that are more reflective of both private and public information. Note that retail noise trade does not directly imply liquidity provision. Retail noise trade can impose risk on other traders (e.g., De Long et al., 1990) or market makers (e.g., Ho and Stoll, 1981). If retail traders are primarily liquidity providers in a static setting, then greater retail activity should be associated with higher EIPAR and ERCs, and less PEAD, which is inconsistent with our findings.

5.2.2 Dynamic noise trade and informed trader response

Banerjee and Breon-Drish (2020) develop a model featuring a potentially informed trader who acquires information dynamically and trades on it via a market maker who also receives liquidity demand with stochastic but persistent volatility. Supporting the persistent volatility assumption, Barber et al. (2008) show that retail investors' trades are highly persistent. In Banerjee and Breon-Drish (2020), the informed trader optimally gathers information more intensely when liquidity demand is more volatile, which tends to improve the information in stock prices in periods with high liquidity trade. Additionally, the informed trader's information is impounded into price gradually, to mitigate price impact, which leads to drift in the direction of the information. Interpreting information acquisition as a manifestation of paying attention to earnings announcements, which makes public disclosures act more like private information (see, e.g., Blankespoor et al., 2020), allows us to apply the predictions of Banerjee and Breon-Drish (2020) around earnings announcements.[19] When retail trade is high, if retail traders provide liquidity to dynamically optimizing informed traders, then the informed traders' information acquisition and trading can lead to stronger ERCs and PEAD. Prior to earnings announcements, when the earnings signal is not available, retail-trade-as-noise simply reduces EIPAR.

[19] Relatedly, Cho (2020) show that an asset that is subject to large demand distortions attract a greater arbitrage position, which leads to short-term abnormal returns.

Notably, our main evidence is consistent with this theory involving retail trade as dynamic noise/liquidity providers. In this narrative, we would not expect retail trade to be directionally aligned with returns around the earnings announcement, as this would conflict with retail-trade-as-noise. Additionally we might expect the effect to be stronger when arbitrageurs face weaker constraints or costs on trading on their information. Arbitrage costs are likely to be lower for buy trades on positive earnings surprises than short trades on negative surprises, such that we would expect stronger effects around positive earnings surprises.

5.3 Retail traders are particularly attention-driven

A large and growing literature focuses on investor attention. Naturally, for investors to react to information, they have to pay attention to it. Narratives focusing on investor attention can broadly be classified as either entirely behavioral or constrained-rational. On the behavioral side, studies have highlighted the potential for investor distraction to reduce attention to earnings announcements (e.g., DellaVigna and Pollet, 2009; Hirshleifer et al., 2009; Diamond et al., 2016). Similarly, excess attention can enhance trading activity (Cahill et al., 2021), but the attention can lead to trading (often buying) independent of the underlying information on average (e.g., Hirshleifer et al., 2008; Michels, 2021). Constrained-rational models, in contrast, explicitly allow investors to choose what to pay attention to, but impose costs of such attention (possibly opportunity costs) that limit the use of information in equilibrium (e.g., Hirshleifer and Teoh, 2003; Sims, 2003; Stijn and Veldkamp, 2010).[20]

Regardless of the underlying mechanisms (i.e., distraction or constrained-rationality), inattention to an earnings announcement will cause the announcement to have weaker effects on stock prices. Subsequent attention to the news can cause PEAD. DellaVigna and Pollet (2009) and Hirshleifer et al. (2009) show that prices respond more weakly to earnings surprises when investors are likely to be distracted. The underreaction they document is followed by PEAD, implying a subsequent correction of the underreaction. If retail investors

[20]See Blankespoor et al. (2020) for a review of literature discussing various costs investors face when obtaining and processing disclosures, and how these costs affect market outcomes.

are more subject to attention effects than other investors, then increased retail trade around an earnings announcement is likely to reflect increased attention to the earnings news. This, via the *attention* narrative, would cause retail trade to be associated with stronger ERCs, less PEAD, and pre-EA returns that reflect more of the upcoming earnings information (higher EIPAR). This pattern is inconsistent with our findings

5.4 Retail traders are overconfident

Traders can be overconfident about their trading abilities or, relatedly, the quality of the information they receive. Daniel et al. (1998) develop a model where overconfident investors view their private information as being better than it really is, leading to overreaction that is subsequently corrected.[21] In their model, investors rationally process public information, which corrects the initial overreaction over time. Overconfidence in some (i.e., private) signals can also lead investors to under-weight other (i.e., public) signals. Lihong (2003) finds that investors are insufficiently responsive to the quality of public signals. Overconfidence can also generally lead to more and worse trading. Barber and Odean (2001) use gender as a proxy for overconfidence and find that men, who are likely to be characterized by greater overconfidence, trade more and earn lower returns than women.

The effects of retail investor overconfidence depend crucially on several other features (e.g., correlation between private signals, and the degree of over- or under-confidence with regard to public signals such as earnings forecasts and announcements). A susceptible investor model, detailed next, might be seen as one in which retail traders are overconfident about uninformative signals prior to the earnings announcement but correctly interpret publicly announced earnings information. This contrasts with a setting in which investors are overconfident about private signals and under-weight public earnings information, or in which investors are overconfident about noisy but informative private signals. Given the potential for narratives building on overconfidence to provide differing predictions related to ERCs,

[21] They also discuss the attribution bias which can facilitate overconfidence when confirmatory signals are overweighted relative to contrary signals.

PEAD, and EIPAR, we note that overconfidence among retail traders could be consistent with our results, but would require further refinement regarding what signals retail traders are overconfident about. We leave such refinements for future work, noting that our evidence is inconsistent at least with the most prominent theories of retail traders either being overconfident about public signals (implying higher ERC and lower PEAD) or private noisy signals (lower ERC and higher PEAD) around earnings announcements.

5.5 Susceptible retail traders

One particular manifestation of retail trader overconfidence is a model of retail traders as 'susceptible' investors, who use public signals but are susceptible to decision influences that are independent of asset fundamentals or the true payoff characteristics (see, e.g., the model in the Appendix of Bushee and Friedman (2016)). In such a model, retail trading around an earnings announcement is likely to rely on and react to earnings as a public salient source of information. In other periods, e.g., before the earnings announcement, retail traders' activity might be governed more by non-fundamental or noise signals that they interpret as informative. Still, there may be non-fundamental signals around the earnings announcement that retail traders react to as well, which can impede a full reaction to the earnings announcement and allow for PEAD.

Under the *susceptible* narrative, retail trade affects the pre-earnings price, as retail trade based on uninformative signals essentially adds noise to price and reduces the degree to which informed traders' private information about upcoming earnings is reflected in price. Around the announcement, because retail investors largely interpret earnings correctly, the earnings announcement returns will be more correlated with announced earnings when there are more retail traders active in the stock. This can reduce the potential for PEAD. However, noise impounded during the announcement by retail traders can also facilitate incomplete impounding of earnings information and PEAD. Crucially, the *susceptible* investor narrative as described implies that retail investors trade on uninformative signals, but that better availability of information reduces their reliance on these signals (as in Bushee and Friedman (2016)). Overall, the *susceptible* narrative predicts that retail activity is associated with higher ERCs, potentially higher or lower PEAD, and lower EIPAR. This is potentially consistent with our pattern of results. Further supporting evidence would show that retail trade is directionally aligned with returns around the earnings announcement.

5.6 Retail traders are relatively informed

The narratives discussed so far portray retail investors, if anything, as prone to making trading decisions in ways that do not reflect fundamentals, either by assumption (i.e., as noise traders), due to inattention or excessive attention, or based on incorrect beliefs about signals. Alternatively, retail investors may be relatively informed. Using proprietary NYSE data that provides aggregate daily buy and sell orders originating from individuals, Kaniel et al. (2012) show that individual trades *before* the earnings announcement predict both earnings announcement window returns and drift. Kelley and Tetlock (2013) use proprietary data from two over-the-counter market centers to show that retail market orders predict both near-term returns and news, including earnings announcements, while retail limit orders provide liquidity.[22] Both Kaniel et al. (2012) and Kelley and Tetlock (2013) interpret their evidence as consistent with individuals having private information and providing liquidity, but do not focus on retail investors' effects on the incorporation of public information.

If retail investors are relatively informed *prior* to the earnings announcement, we should expect lower ERCs and greater EIPAR when retail traders are more active. PEAD should also be lower when there is greater informed retail trade prior to and around the earnings announcement. This is inconsistent with our main findings, suggesting that retail traders are not, on average, best treated as informed traders.

[22] Aboody et al. (2010) find that price increases in the 12 months prior to an earnings announcement are associated with positive (negative) returns during (following) the earnings announcement. They attribute their result at least in part to individual investor attention attracted to high pre-announcement returns.

6 Additional analyses

This section presents additional analyses that seek to distinguish between the theories supported by the evidence in Section 4, as well as tests that provide further support and show robustness to alternative specifications or sample cuts.

6.1 Buy-sell imbalance

Our main evidence is potentially consistent with theories involving dynamic liquidity provision in the presence of informed trade and with susceptible investors. Notably, these differ in their predictions about the alignment of retail trade with returns around the earnings announcement. To differentiate between these, we examine the announcement-window retail order imbalance, i.e., the propensity of retail traders to buy rather than sell, around earnings announcements. Retail order imbalance is defined as

$$Retail\ OIB_{i,t} = \frac{\text{Retail Buys}_{i,t} - \text{Retail Sales}_{i,t}}{\text{Retail Buys}_{i,t} + \text{Retail Sales}_{i,t}}.$$

We re-estimate our ERC and PEAD regressions from Tables 5 and 6 but with Retail OIB replacing log retail volume as the independent variable of interest. We also include interactions between SUE and Retail OIB for consistency with prior tables, though our focus is on the main effect of Retail OIB. Table 8 shows that retail order imbalance is not generally associated with returns during the earnings announcement window, which suggests that retail traders are not generally trading in a directional manner that supports ERCs or affects PEAD. Figures 3 and 4 show that retail buy-sell imbalance is generally similar for positive and negative earnings surprises, and within large and small subsamples. In the four series plotted across the two figures, retail buy-sell imbalance is mildly negative except for a spike leading up to the earnings announcement. The evidence in Table 8 and Figures 3 and 4 pushes us towards a dynamic liquidity provision interpretation of the main results rather than one in which retail traders are themselves responding to public signals, even if they are susceptible to non-informative signals.

6.2 Positive and negative earnings surprise subsamples

Trading on negative information is plausibly more costly on average, due to transaction costs associated with short selling (e.g., Gamble and Xu, 2016).[23] Thus, investors' responses to earnings news can be asymmetric. Consistent with this, Figure 5 shows higher volume from retail and nonretail sources around positive surprises compared to negative surprises.

Stronger effects around positive earnings surprises could be consistent with both the dynamic liquidity and susceptible investor theories, with the former driven by lower-cost arbitrage and the latter based on lower-cost retail trade. In light of the results in Table 8 on buy-sell imbalance supporting the dynamic liquidity theory, we view our results regarding differential responses to positive and negative surprises as providing a further test of the dynamic liquidity theory. We re-estimate our ERC and PEAD regressions from Tables 5 and 6 within subsamples based on the sign of the earnings surprise.

Estimates of ERCs within subsamples are shown in Table 9. Positive and significant coefficients on SUE across columns imply that prices respond to both positive and negative earnings news, although the coefficients appear larger for positive surprises. Focusing on our coefficients of interest on the SUE $\times$ Log(Retail) interactions, we find that our effects noted earlier are largely concentrated in positive earnings surprises. For EA-window returns, retail trading is positively associated with ERCs in the positive-SUE subsample ($\beta = 0.181$, $p < 0.01$), but negatively and insignificantly associated with ERCs in the negative-SUE subsample ($\beta = -0.007$, $p > 0.10$). These results support the dynamic liquidity theory.

Table 10 presents subsample results for PEAD. We observe PEAD on average, based on positive and significant coefficients on SUE, only over the 2-to-5 day window (in both positive and negative earnings surprise subsamples). However, retail activity contributes to PEAD for positive surprises only. The coefficient on SUE $\times$ Log(Retail) in column 1 is positive

[23] Kelley and Tetlock (2017) provide supporting evidence that shorts are a only a small percentage of retail trades (around 5.5% of their positions).

($\beta = 0.138$) and significantly different both from zero and from the coefficient on SUE $\times$ Log(Retail) in column 2 ($\beta \approx 0$). Interestingly, EA-window retail trade is also associated with PEAD over the 2-to-next-EA window following positive earnings surprises ($\beta = 0.110$, $p < 0.01$) and marginally associated with PEAD following positive earnings over the 2-to-45 window ($\beta = 0.0736$, $p < 0.10$). Retail trade is not significantly associated with PEAD over any window following negative SUEs. These results suggest that traders mostly react to positive surprises, consistent with a stronger effect of dynamic informed trader attention to earnings in response to increased retail trade when trading on the news is less costly. The persistence of retail trading, both day-to-day and plausibly from one EA to the next, allows potentially capital-constrained arbitrageurs to gradually impound positive earnings news into prices.

6.3 Further analysis and robustness checks

Several additional results are presented in Appendix A. Table A.2 shows that retail activity is not significantly associated with the speed of incorporation of earnings news, supporting a noisy liquidity provision interpretation over a narrative featuring information-based retail trading per se. This is also consistent with the result shown in Figure 1 of Banerjee and Breon-Drish (2020) that the speed with which information is reflected in price is relatively insensitive to model parameters (the cost of information acquisition in their Figure). Table A.3 presents PEAD regressions with EA-window retail trade replaced by PEAD-window retail trade, and finds results consistent with those presented in Table 6.

Tables A.4-A.8 replicate our ERC and PEAD regressions in subsamples. Table A.4 shows that our ERC and PEAD results hold, and display significant PEAD over a longer window, if we limit our sample to extreme earnings announcements (top 2 and bottom 2 quantiles). Table A.5 shows that our ERC and PEAD results hold in a subsample with sub-penny bid-ask spreads where the Boehmer et al. (2021) methodology is more likely to identify retail trades via price improvement (see Barber et al. (2022) for further details).

Table A.6 shows that our ERC and PEAD results are present for both small and big firms, with splits based on market cap. Table A.7 shows that our ERC and PEAD results are concentrated in and stronger on normal EA rather than busy EA days, i.e., days without too many competing earnings announcements. This is consistent with dynamic liquidity in the presence of informed traders who have to choose what to pay attention to (e.g., Hirshleifer et al., 2009; Andrei et al., 2021). Table A.8 shows that our ERC and PEAD results are concentrated on earnings announcements released on Monday through Thursday, rather than Friday. This could be due to arbitrageur distraction on Fridays (e.g., DellaVigna and Pollet, 2009), or driven by the paucity of Friday announcements leading to low power.

Table A.9 is a "reverse" regression of the specification presented in Table 4, with PreRet as the dependent variable and PreRetal interacted with SUE. It shows that foreknowledge of the earnings surprise is more positively associated with pre-announcement returns when retail trade is greater, consistent with the dynamic liquidity provision theory.

Table A.1 supports our use of outages as a negative shock to retail trade using intraday data. Table A.10 shows that our outage-based results are robust to using the number of complaints in lieu of the top-quintile complaint indicator and to entropy balancing to address potential differences between earnings announced on outage days versus non-outage days (descriptives provided in Table A.11). Table A.10 also provides a placebo test with insignificant coefficients of interest when the Outage indicator is replaced with a pseudo-indicator drawn randomly, and this is repeated 1,000 times.

7 Discussion and Conclusion

This study examines how retail trading affects market reactions to corporate earnings announcements using the recently-developed TAQ-based measure of retail trade based on price improvement offered to retail market orders and outages at retail brokerages. Importantly, retail brokerage outages that make it harder for their users to trade are random with respect to earnings news, so we can treat them as exogenous shocks to retail trading frictions and use them to identify plausibly causal effects of retail trade on the pricing of earnings news.

Retail traders potentially impound noise into prices, but can also trade on available information and provide liquidity to other market participants. Our findings suggest that retail activity leads to stronger reactions to earnings announcements, which is consistent with information-based trade or liquidity provision. Additional evidence suggests that this may be driven by pre-EA retail trade reducing the amount of earnings-anticipating information in price and subsequently, during the EA window, trading on publicly released earnings news or providing liquidity to those who do. Additional evidence provides further support for a theory in which retail traders dynamically provide liquidity to potentially informed traders who choose how attentive to be to earnings announcements (Andrei et al., 2021; Banerjee and Breon-Drish, 2020). Our results suggest that whether retail traders' net effect is to impound noise or provide liquidity to informed trade may depend on the availability of public information. Prior to earnings announcements, retail traders and liquidity-takers are plausibly relatively uninformed, given their limited access to resources available to professional and institutional traders or the scarcity of private information about upcoming earnings. Once earnings are announced, traders can access substantial amounts of corporate information, including actual earnings, conference call transcripts, and analysis (e.g., via SeekingAlpha contributors). This information access can facilitate investors' processing of earnings information.

Our results on the relation between retail trade and PEAD extend the findings of Hirshleifer et al. (2008) and Bartov et al. (2000) while complementing those of Michels (2021). Retail trade during the earnings announcement window is associated with higher short-window PEAD both in association tests and in tests where a (lack of) retail trade is exogenously driven by retail brokerage outages. Nonetheless, there is some evidence that retail trade may contribute to PEAD, particularly for positive earnings surprises.

Our findings may differ from prior studies (e.g., our stronger association between retail trade and PEAD relative to Hirshleifer et al. (2008)) because of differences in sample time frame, which brings with it differences in the strength of the PEAD anomaly and the ways that retail traders can access information and trade on it. Prior studies have largely used data from periods in which internet-based stock market information was harder to access (e.g., the early to mid-1990s), and in which the post-earnings announcement drift was a reliable phenomenon. Our results broadly contribute to the emerging non-hegemonic characterization of retail investors as market participants who can either help or hinder the degree to which prices reflect public information (e.g., Aboody et al., 2010; Barber and Odean, 2000; Kaniel et al., 2008, 2012; Kelley and Tetlock, 2013; Ozik et al., 2020; Welch, 2022).

We close by suggesting some potentially interesting avenues for future research. Studies are already using multiple measures of retail activity, including the Boehmer et al. (2021) proxy and proxies based on Robinhood holdings to examine reactions to non-earnings announcements (e.g., Moss et al., 2020), but could examine whether and how retail traders facilitate information transfer across firms. Additionally, the effects of retail trading are likely to be contextual, differing across heterogeneous institutional environments. We believe further attention is merited to identify contextual features that separately encourage or discourage noise, liquidity provision, or information-based trade. Theoretical studies might provide insight into how the differing effects of retail traders in different settings affect aggregate efficiency and incentives to acquire information. Additional theory and evidence on how firms optimize their disclosures in the face of retail investors who are not just noise traders seems warranted.

Figures

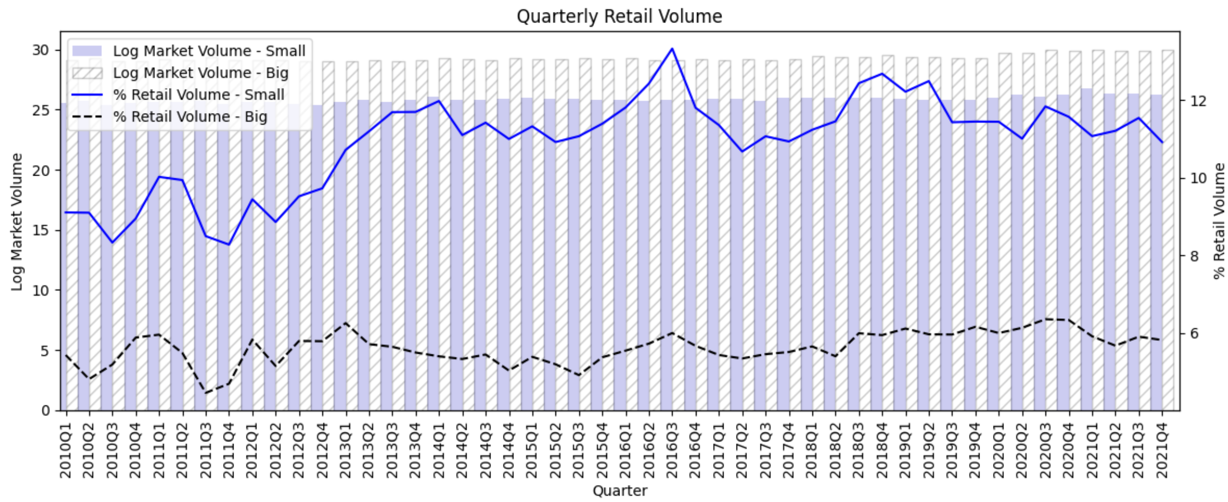

Figure 1: Quarterly Market Volume (share value traded) and % Retail Volume for small and big firm subsamples. Small and big designations are based on a median split on market value of equity.

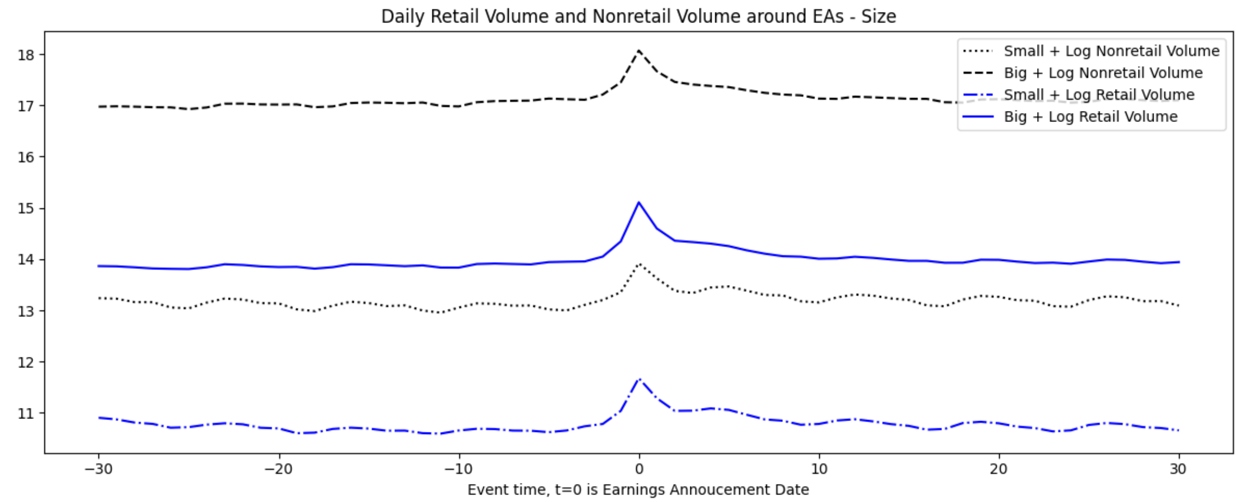

Figure 2: Daily Retail and Nonretail Volume around earnings announcements for small and big firm subsamples. Small and big designations are based on a median split on market value of equity.

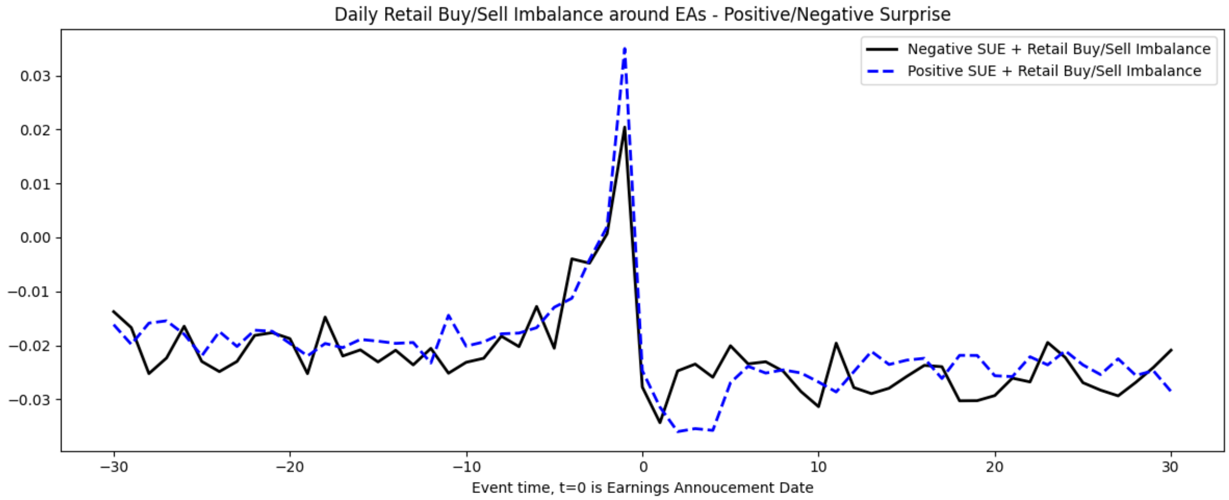

Figure 3: Daily Retail buy-sell imbalance around earnings announcements for positive and negative earnings surprises.

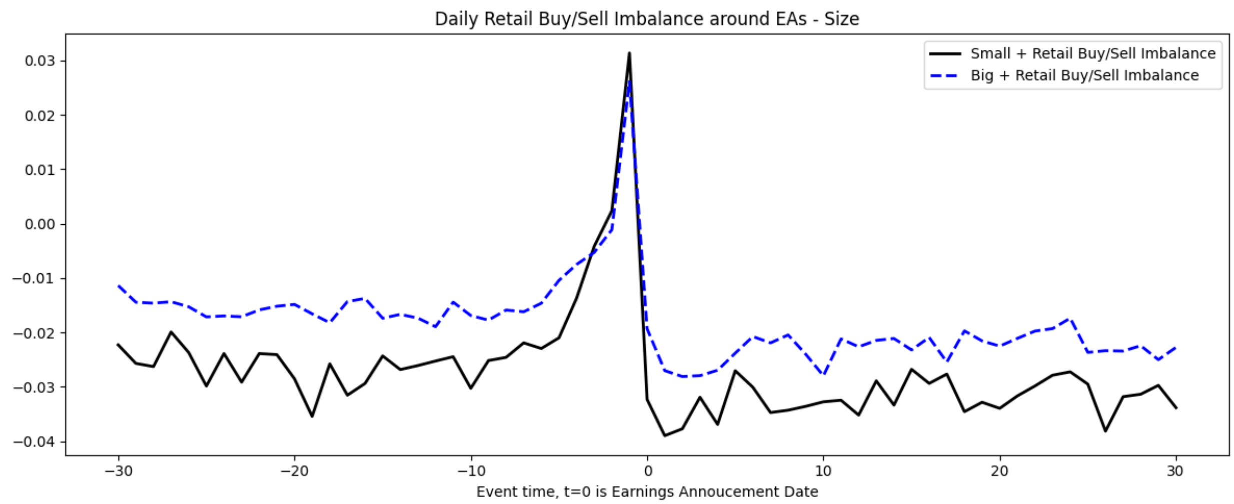

Figure 4: Daily Retail buy-sell imbalance around earnings announcements for small and big firm subsamples. Small and big designations are based on a median split on market value of equity.

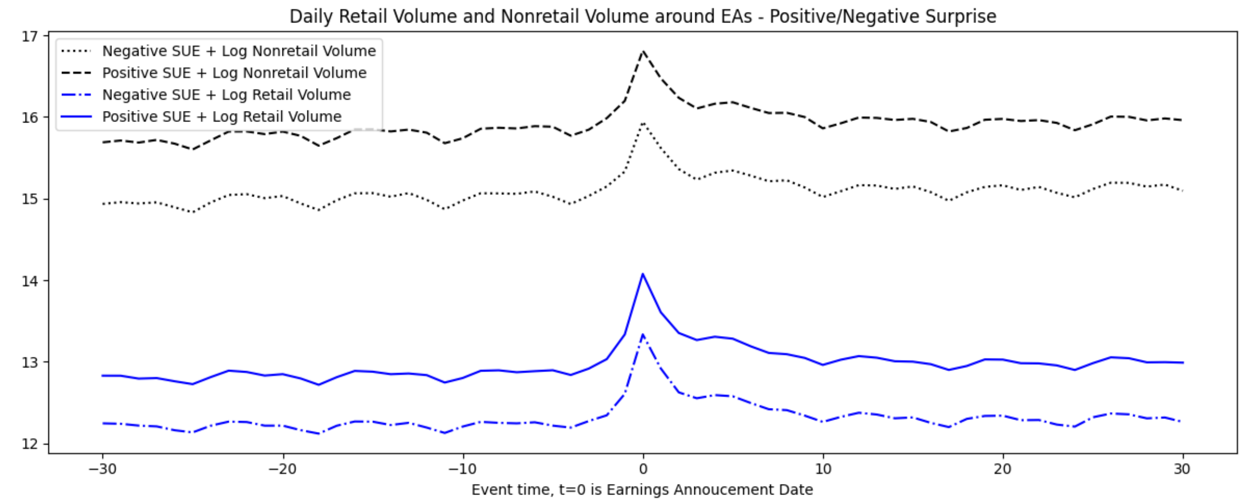

Figure 5: Daily Retail and Nonretail Volume around earnings announcements for positive and negative earnings surprises.

Tables

Table 1: Sample selection

	Sample selection for analyses
	# Firm-Earnings Announcements
Compustat and CRSP sample	213,601
Less: missing controls, IBES data, returns and trading volume	77,550
Less: firms that are not listed on Nasdaq/NYSE/AMEX	38,974
	Final Sample
Unique firms	4,218
Unique earnings announcements	97,077

Table 2: Descriptive Statistics

	mean	sd	min	max	N
SUE(raw)	-0.00	0.09	-13.20	1.95	97077
SUE	6.88	3.06	1.00	11.00	97077
BHAR[0,1]	-0.03	0.10	-0.19	0.14	97077
BHAR[2,5]	-0.06	0.17	-0.34	0.22	97077
BHAR[2,22]	-0.65	1.07	-2.79	0.63	97077
BHAR[2,45]	-1.66	2.45	-7.22	0.68	97077
BHAR[2,next]	-0.54	1.00	-2.87	0.43	97077
Log(Retail)	14.19	2.18	1.56	22.87	97077
Log(Nonretail)	16.86	2.31	0.00	24.11	97077
#Complaints	73.90	963.91	0.00	28247.00	97077
PreRetail	15.81	1.99	8.62	24.72	97077
PreNonretail	18.53	2.18	10.10	26.15	97077
Log(MktVol)	16.95	2.27	5.17	24.31	97077
PreRet	0.01	0.10	-0.80	4.75	97077
Log(Size)	7.35	1.87	1.56	14.66	97077
Book-to-Market	0.54	0.61	-20.45	56.96	97077
EPersistence	0.17	0.36	-0.89	1.10	97077
EVOL	1.82	6.99	0.03	65.37	97077
ERepLag	35.62	12.36	-7.00	100.00	97077
#Estimates	9.08	7.10	1.00	51.00	97077
TURN	24.28	182.64	0.27	25195.29	97077
Loss	0.30	0.46	0.00	1.00	97077
#Announcements	142.52	90.70	1.00	408.00	97077
IO	0.57	0.37	0.00	1.00	97077

Notes: This table presents descriptive statistics for the sample. Detailed definitions of all variables are included in Appendix B.

Table 3: Correlations

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
1 SUE	1.000																						
2 BHAR[0,1]	0.179***	1.000																					
3 BHAR[2,5]	0.113***	0.916***	1.000																				
4 BHAR[2,22]	0.007*	0.477***	0.558***	1.000																			
5 BHAR[2,45]	-0.001	0.322***	0.376***	0.782***	1.000																		
6 BHAR[2,next]	-0.011***	0.481***	0.537***	0.215***	0.176***	1.000																	
7 Log(Retail)	0.103***	-0.030***	-0.034***	0.014***	0.053***	-0.070***	1.000																
8 Log(Nonretail)	0.113***	-0.019***	-0.024***	0.026***	0.060***	-0.069***	0.940***	1.000															
9 #Complaints	0.006	-0.016***	-0.016***	-0.038***	-0.051***	-0.029***	0.021***	0.020***	1.000														
10 PreRetail	0.087***	-0.036***	-0.037***	0.018***	0.046***	-0.080***	0.957***	0.923***	0.022***	1.000													
11 PreNonretail	0.101***	-0.021***	-0.024***	0.029***	0.056***	-0.074***	0.908***	0.977***	0.018***	0.944***	1.000												
12 Log(MktVol)	0.113***	-0.022***	-0.027***	0.023***	0.061***	-0.071***	0.951***	0.999***	0.022***	0.931***	0.976***	1.000											
13 PreRet	0.169***	0.062***	-0.016***	-0.087***	-0.073***	-0.081***	0.057***	0.051***	-0.000	0.058***	0.051***	0.053***	1.000										
14 Log(Size)	0.100***	-0.015***	-0.016***	0.043***	0.077***	-0.081***	0.804***	0.889***	0.025***	0.839***	0.920***	0.884***	0.006	1.000									
15 Book-to-Market	-0.030***	0.008**	-0.000	-0.031***	-0.057***	-0.013***	-0.207***	-0.234***	-0.004	-0.184***	-0.212***	-0.236***	0.030***	-0.260***	1.000								
16 EPersistence	0.006	-0.010**	-0.011***	-0.004	-0.015***	-0.008*	0.048***	0.038***	-0.000	0.050***	0.033***	0.039***	0.004	0.002	-0.043***	1.000							
17 EVOL	-0.027***	-0.013***	-0.011***	-0.007*	-0.013***	-0.020***	-0.038***	-0.070***	-0.005	-0.027***	-0.068***	-0.063***	-0.027***	-0.098***	0.107***	-0.047***	1.000						
18 ERepLag	-0.096***	-0.030***	-0.033***	-0.047***	-0.022***	0.042***	-0.305***	-0.361***	0.010***	-0.301***	-0.362***	-0.357***	-0.002	-0.394***	0.083***	-0.037***	0.062***	1.000					
19 #Estimates	0.074***	-0.020***	-0.019***	0.032***	0.048***	-0.030***	0.694***	0.719***	0.004	0.723***	0.737***	0.721***	0.012***	0.715***	-0.137***	0.077***	-0.031***	-0.303***	1.000				
20 TURN	0.008*	-0.006*	-0.006	-0.016***	-0.017***	-0.011***	0.036***	0.021***	0.002	0.037***	0.016***	0.024***	0.037***	-0.021***	-0.003	0.019***	0.091***	0.019***	0.010**	1.000			
21 Loss	-0.211***	-0.066***	-0.047***	-0.036***	-0.032***	0.029***	-0.233***	-0.303***	0.009**	-0.234***	-0.319***	-0.294***	-0.070***	-0.366***	0.072***	-0.008**	0.130***	0.244***	-0.198***	0.032***	1.000		
22 #Announcements	0.020***	0.015***	0.023***	0.052***	0.032***	-0.018***	-0.034***	0.028***	-0.022***	-0.039***	0.015***	0.030***	-0.029***	0.058***	-0.010**	-0.002	-0.014***	-0.263***	-0.035***	-0.009**	0.014***	1.000	
23 IO	0.039***	0.003	-0.003	-0.040***	0.062***	0.036***	0.233***	0.291***	0.020***	0.172***	0.252***	0.292***	0.005	0.273***	-0.104***	-0.068***	-0.064***	-0.100***	0.101***	-0.020***	-0.040***	0.073***	1.000

Notes: This table presents Pearson correlations. Detailed definitions of all variables are included in Appendix B. ***, **, and * indicate statistical significance at two-sided 1%, 5%, and 10% levels, respectively.

Table 4: Earnings Surprises and Pre-EA Retail Trading Volume

	SUE	
	(1)	(2)
PreRetail	0.0330	0.0226
	(0.0266)	(0.0271)
PreRetail × PreRet	-0.151***	-0.146***
	(0.0156)	(0.0149)
PreNonretail	-0.0570*	-0.0347
	(0.0334)	(0.0402)
PreNonretail × PreRet	0.146***	0.144***
	(0.0160)	(0.0152)
PreRet	0.198***	0.185***
	(0.0113)	(0.0117)
Controls	No	Yes
Year-Quarter FE	Yes	Yes
Day-of-Week FE	Yes	Yes
Firm FE	Yes	Yes
Observations	97077	97077
Adj.R2	0.140	0.170

This table presents results of returns and PreRetail in the 10-day window before earnings announcements on earnings surprise deciles. All independent variables are standardized to be mean-zero and unit-variance. Control variables include PreRet, Log(Size), Book-to-Market , EVOL, EPersistence, ERepLag, #Estimates, TURN, Loss, #Announcements, IO, and PreNonretail. Detailed definitions of all variables are included in Appendix B. Standard errors and coefficients are clustered by firm and quarter. ***, **, and * indicate statistical significance at two-sided 1%, 5%, and 10% levels, respectively.
Regression model: $SUE_{it} = \beta_0 + \beta_1 PreRetail_{it} + \beta_2 PreRet_{it} + \beta_3 PreRetail_{it} * PreRet_{it} + \sum \beta_k X_{k,it} + \epsilon_{it}$

Table 5: Earnings Announcement Returns and Retail Trading Volume

	BHAR[0,1]	
	(1)	(2)
SUE	0.210***	0.170***
	(0.00867)	(0.00676)
Log(Retail)	-0.0848**	-0.148***
	(0.0419)	(0.0416)
SUE × Log(Retail)	0.130***	0.0924***
	(0.0143)	(0.0151)
Log(Nonretail)	0.0340	0.141**
	(0.0505)	(0.0538)
SUE × Log(Nonretail)	-0.0360**	0.160***
	(0.0137)	(0.0180)
PreRet		0.131***
		(0.0182)
Controls	No	Yes
Controls*SUE Decile	No	Yes
Year-Quarter FE	Yes	Yes
Day-of-Week FE	Yes	Yes
Firm FE	Yes	Yes
Observations	97077	97077
Adj.R2	0.281	0.311

This table presents results of regressions of earnings announcement returns (BHAR[0,1]) on earnings surprise quantiles interacted with the log(Retail Volume) during the earnings announcement window. All independent variables are standardized to be mean-zero and unit-variance. Control variables include PreRet, Log(Size), Book-to-Market , EVOL, EPersistence, ERepLag, #Estimates, TURN, Loss, #Announcements, IO, and Log(Nonretail). Detailed definitions of all variables are included in Appendix B. Standard errors and coefficients are clustered by firm and quarter. ***, **, and * indicate statistical significance at two-sided 1%, 5%, and 10% levels, respectively.

Regression model: $BHAR[0,1]_{it} = \beta_0 + \beta_1 SUE_{it} + \beta_2 Log(Retail)_{it} + \beta_3 SUE_{it} * Log(Retail)_{it} + \sum \beta_k X_{k,it} + \sum \beta_k SUE_{it} * X_{k,it} + \epsilon_{it}$

Table 6: Earnings Announcement Returns, Post-earnings Announcement Drift, and Retail Trading

	BHAR[0,1]	*BHAR[2,5]*	*BHAR[2,22]*	*BHAR[2,45]*	*BHAR[2,next]*
	(1)	(2)	(3)	(4)	(5)
SUE	0.170***	0.109***	0.0126***	0.00362	0.00229
	(0.00676)	(0.00627)	(0.00423)	(0.00404)	(0.00523)
Log(Retail)	-0.148***	-0.130***	-0.0293	0.00343	-0.0610**
	(0.0416)	(0.0384)	(0.0356)	(0.0273)	(0.0279)
SUE × Log(Retail)	0.0924***	0.0525***	0.0134	0.0130	0.00973
	(0.0151)	(0.0142)	(0.00986)	(0.0111)	(0.0141)
Log(Nonretail)	0.141**	0.136**	0.0723	0.0441	0.0671
	(0.0538)	(0.0551)	(0.0509)	(0.0415)	(0.0466)
SUE × Log(Nonretail)	0.160***	0.111***	0.0239*	0.00169	0.0408**
	(0.0180)	(0.0173)	(0.0133)	(0.0144)	(0.0190)
PreRet	0.131***	0.0686***	-0.00938	-0.000100	-0.0214
	(0.0182)	(0.0173)	(0.0158)	(0.0133)	(0.0150)
Controls	Yes	Yes	Yes	Yes	Yes
Controls*SUE Decile	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes
Day-of-Week FE	Yes	Yes	Yes	Yes	Yes
Observations	97077	97077	97077	97077	97077
Adj.R2	0.311	0.362	0.531	0.572	0.388

Notes: This table presents results of regressions of earnings announcement returns over different windows on earnings surprise quantiles interacted with Log(Retail). All variables are standardized to be mean-zero and unit-variance. Control variables include PreRet, Log(Size), Book-to-Market, EVOL, EPersistence, ERepLag, #Estimates, TURN, Loss, #Announcements, IO, and Log(Nonretail). Detailed definitions of all variables are included in Appendix B. Standard errors are clustered by firm and quarter. ***, **, and * indicate statistical significance at two-sided 1%, 5%, and 10% levels, respectively.
Regression model: $BHAR[a,b]_{it} = \beta_0 + \beta_1 SUE_{it} + \beta_2 Log(Retail)_{it} + \beta_3 SUE_{it} * Log(Retail)_{it} + \sum \beta_k X_{k,it} + \sum \beta_k SUE_{it} * X_{k,it} + \epsilon_{it}$

Table 7: Earnings Announcement Returns, Post-earnings Announcement Drift, and Retail Frictions

	BHAR[0,1]	*BHAR[2,5]*	*BHAR[2,22]*	*BHAR[2,45]*	*BHAR[2,next]*
	(1)	(2)	(3)	(4)	(5)
SUE	0.152***	0.0844***	0.00960	0.00464	0.00868
	(0.00888)	(0.00824)	(0.00762)	(0.00825)	(0.00944)
Outage	0.126***	0.0996***	0.00270	-0.120***	-0.0399
	(0.0293)	(0.0280)	(0.0284)	(0.0328)	(0.0391)
Outage × SUE	-0.0613**	-0.0460*	-0.0136	0.00775	-0.00594
	(0.0286)	(0.0258)	(0.0270)	(0.0317)	(0.0335)
Log(MktVol)	0.00412	0.00929	0.0541***	0.0832***	-0.0356
	(0.0248)	(0.0223)	(0.0182)	(0.0192)	(0.0262)
PreRet	0.109***	0.0623***	-0.00647	-0.000248	-0.00787
	(0.00764)	(0.00634)	(0.00547)	(0.00556)	(0.00587)
Controls	Yes	Yes	Yes	Yes	Yes
Controls*SUE Decile	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes
Day-of-Week FE	Yes	Yes	Yes	Yes	Yes
Observations	31860	31860	31860	31860	31860
Adj.R2	0.390	0.473	0.615	0.612	0.515

This table presents results of regressions of earnings announcement returns over different windows on earnings surprise quantiles interacted with broker outages. All variables are standardized to be mean-zero and unit-variance. Control variables include Log(MktVol), PreRet, Log(Size), Book-to-Market, EVOL, EPersistence, ERepLag, #Estimates, TURN, Loss, #Announcements, IO. Detailed definitions of all variables are included in Appendix B. Standard errors are clustered by firm and quarter. ***, **, and * indicate statistical significance at two-sided 1%, 5%, and 10% levels, respectively.

Regression model: $BHAR[a,b]_{it} = \beta_0 + \beta_1 Outage_t + \beta_3 SUE_{it} * Outage_t + \sum \beta_k X_{k,it} + \sum \beta_k SUE_{it} * X_{it} + \epsilon_{it}$

Table 8: Retail Order Imbalance

	BHAR[0,1]	*BHAR[2,5]*	*BHAR[2,22]*	*BHAR[2,45]*	*BHAR[2,next]*
	(1)	(2)	(3)	(4)	(5)
SUE	0.164***	0.105***	0.0118***	0.00350	0.0216***
	(0.00662)	(0.00612)	(0.00428)	(0.00411)	(0.00529)
Retail OIB	-0.0140*	-0.00884	-0.00212	-0.000134	-0.00730
	(0.00730)	(0.00572)	(0.00376)	(0.00342)	(0.00555)
SUE × Retail OIB	-0.00406	-0.000714	-0.000661	0.00548*	0.00451
	(0.00420)	(0.00440)	(0.00313)	(0.00297)	(0.00464)
Log(MktVol)	-0.0314	-0.0165	0.0385	0.0489*	-0.00591
	(0.0399)	(0.0305)	(0.0244)	(0.0258)	(0.0247)
PreRet	0.132***	0.0686***	-0.00937	-0.0000182	-0.0215
	(0.0183)	(0.0175)	(0.0158)	(0.0134)	(0.0151)
Controls	Yes	Yes	Yes	Yes	Yes
Controls*SUE Decile	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes
Day-of-Week FE	Yes	Yes	Yes	Yes	Yes
Observations	97077	97077	97077	97077	97077
Adj.R2	0.310	0.361	0.531	0.572	0.388

This table presents results of regressions of earnings announcement returns over different windows on earnings surprise quantiles interacted with retail net buying scaled by shares outstanding. All variables are standardized to be mean-zero and unit-variance. Control variables include Log(MktVol), PreRet, Log(Size), Book-to-Market, EVOL, EPersistence, ERepLag, #Estimates, TURN, Loss, #Announcements, IO. Detailed definitions of all variables are included in Appendix B. Standard errors are clustered by firm and quarter. ***, **, and * indicate statistical significance at two-sided 1%, 5%, and 10% levels, respectively.
Regression model: $BHAR[a,b]_{it} = \beta_0 + \beta_1 SUE_{it} + \beta_2 RetailOIB_{it} + \beta_3 SUE_{it} * RetailOIB_{it} + \sum \beta_k X_{k,it} + \sum \beta_k SUE_{it} * X_{k,it} + \epsilon_{it}$

Table 9: Subsample Analysis of ERCs by SUE sign

	BHAR[0,1]	
	Positive	Negative
	(1)	(2)
SUE	0.246***	0.173***
	(0.0222)	(0.0250)
Log(Retail)	-0.162**	-0.350***
	(0.0652)	(0.101)
SUE × Log(Retail)	0.181***	-0.00698
	(0.0444)	(0.0619)
Log(Nonretail)	0.122	-0.148
	(0.0894)	(0.133)
SUE × Log(Nonretail)	0.195***	-0.0636
	(0.0684)	(0.0809)
Controls	Yes	Yes
Controls*SUE Decile	Yes	Yes
Year-Quarter FE	Yes	Yes
Day-of-Week FE	Yes	Yes
Firm FE	Yes	Yes
Observations	55704	27865
Adj.R2	0.297	0.333
	Difference in SUE × Log(Retail) coefficients	
	0.188***	

Notes: This table presents results of regressions of earnings announcement returns over different windows on earnings surprise quantiles interacted with Log(Retail). The sample is split by the sign of earnings surprises. All variables are standardized to be mean-zero and unit-variance. Control variables (suppressed) include PreRet, Log(Size), Book-to-Market, EVOL, EPersistence, ERepLag, #Estimates, TURN, Loss, #Announcements, IO, and Log(Nonretail). Detailed definitions of all variables are included in Appendix B. Standard errors are clustered by firm and quarter. ***, **, and * indicate statistical significance at two-sided 1%, 5%, and 10% levels, respectively. Statistical significance for differences in coefficients across subsamples is evaluated based on the standard errors of the coefficient on the interaction of SUE × Log(Retail) $\times 1_{right}$ where 1_{right} is an indicator for the right subsample condition, in a fully interacted specification, i.e., we allow each variable, including the fixed effects, to vary by the partitioning variable and drop observations that do not fall into either partition if relevant.
Regression model: $BHAR[a,b]_{it} = \beta_0 + \beta_1 SUE_{it} + \beta_2 Log(Retail)_{it} + \beta_3 SUE_{it} * Log(Retail)_{it} + \sum \beta_k X_{k,it} + \sum \beta_k SUE_{it} * X_{k,it} + \epsilon_{it}$

Table 10: Subsample analyses of PEAD by SUE sign

	Panel A: negative/positive surprises							
	BHAR[2,5]		*BHAR[2,22]*		*BHAR[2,45]*		*BHAR[2,next]*	
	Positive	Negative	Positive	Negative	Positive	Negative	Positive	Negative
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SUE	0.168***	0.118***	-0.0109	-0.0162	-0.0165	-0.0256	0.0262	0.00624
	(0.0230)	(0.0238)	(0.0169)	(0.0206)	(0.0168)	(0.0226)	(0.0286)	(0.0279)
Log(Retail)	-0.151**	-0.249**	-0.0531	-0.0182	-0.0513	0.0396	-0.120**	-0.0571
	(0.0590)	(0.105)	(0.0609)	(0.0923)	(0.0499)	(0.0800)	(0.0502)	(0.107)
SUE × Log(Retail)	0.138***	0.000329	0.0479	0.00877	0.0736*	0.0143	0.110***	0.0187
	(0.0386)	(0.0651)	(0.0446)	(0.0627)	(0.0420)	(0.0537)	(0.0404)	(0.0721)
Log(Nonretail)	0.0852	-0.0376	0.0757	-0.0185	0.0947	-0.00104	0.0409	-0.122
	(0.0910)	(0.134)	(0.0785)	(0.117)	(0.0636)	(0.116)	(0.0810)	(0.157)
SUE × Log(Nonretail)	0.142**	-0.0437	0.0156	-0.0326	-0.0420	-0.000944	0.0243	-0.107
	(0.0641)	(0.0859)	(0.0612)	(0.0852)	(0.0615)	(0.0808)	(0.0588)	(0.102)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls*SUE Decile	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	55704	27865	55704	27865	55704	27865	55704	27865
Adj.R2	0.354	0.395	0.534	0.547	0.588	0.564	0.420	0.372
	Difference in SUE × Log(Retail Volume) coefficients							
	0.138**		0.03913		0.0593		0.0913*	
	(0.0759)		(0.0824)		(0.0753)		(0.0733)	

Notes: This table presents results of regressions of earnings announcement returns over different windows on earnings surprise quantiles interacted with Log(Retail). The sample split is based on signed earnings surprises. All independent variables are standardized to be mean-zero and unit-variance. Control variables (suppressed) include PreRet, Log(Size), Book-to-Market, EVOL, EPersistence, ERepLag, #Estimates, TURN, Loss, #Announcements, IO, and Log(Nonretail). Detailed definitions of all variables are included in Appendix B. Standard errors are clustered by firm and quarter. ***, **, and * indicate statistical significance at two-sided 1%, 5%, and 10% levels, respectively. Statistical significance for differences in coefficients across subsamples is evaluated based on the standard errors of the coefficient on the interaction of SUE × Log(Retail) $\times 1_{right}$ where 1_{right} is an indicator for the right subsample condition, in a fully interacted specification, i.e., we allow each variable, including the fixed effects, to vary by the partitioning variable and drop observations that do not fall into either partition if relevant.
Regression model: $BHAR[a,b]_{it} = \beta_0 + \beta_1 SUE_{it} + \beta_2 Log(Retail)_{it} + \beta_3 SUE_{it} * Log(Retail)_{it} + \sum \beta_k X_{k,it} + \sum \beta_k SUE_{it} * X_{k,it} + \epsilon_{it}$

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A Additional analysis

This section presents results involving the speed of reaction to earnings information based on intraday returns measures, trading during PEAD windows, additional subsample analyses, outage-related robustness and placebo checks, and descriptive statistics for earnings released on days with versus without brokerage outages.

In intraday tests, we focus on 5-minute intervals around earnings announcements. For announcements made outside of trading hours, we examine the first 5-minute intervals after markets open on the adjusted earnings announcement date. $IPT_{adj}[0,5]$ is the adjusted intraperiod price timeliness measure, calculated as

$$IPT_{adj}[0,5] = \sum_{i=0}^{5} \left(1 - \frac{|BHAR_5 - BHAR_i|}{|BHAR_5|}\right).$$

Adjusted IPT is an improvement over traditional measures of IPT as it penalizes over-reactions and reversals (Blankespoor et al., 2020). In intraday analyses,relative price discovery (see, e.g., Bochkay et al., 2020) is an additional measure related to how retail trading affects the speed with which prices incorporate public information. Relative price discovery is defined at the firm-5-minute-interval level as:

$$\mathrm{RPD}_{i,t} = \frac{\log(1 + \mathrm{ret}_{i,t})}{\log(1 + \mathrm{ret}_{i,EA})} \tag{6}$$

where $ret_{i,t}$ is a firm's return during a 5-minute interval, based on TAQ midpoints, and $ret_{i,EA}$ is the earnings announcement return. RPD helps identify which sub-intervals feature the incorporation of information revealed in aggregate over a longer time interval.

Retail[a,b] and NonRetail[a,b] represent aggregate retail and nonreatail trade, respectively, from day a through day b relative to the earnings announcement window (day 0), inclusive.

Table A.1: Retail Trading Volume and Brokerage Outages

	Log(Retail)	
	(1)	(2)
Outage	-0.00570**	-0.00412**
	(0.00281)	(0.00203)
Log(NonRetail)		0.283***
		(0.00667)
Time-of-Day FE	Yes	Yes
Firm FE	Yes	Yes
Observations	13823032	13823032
Adj.R2	0.571	0.595

This table presents results of regressions of Log(Retail) on brokerage outages. The sample includes 5-min intervals during outages, matched with intervals 1 trading day before and after for the same stock and time of the day. In Column (2), we control for Log(NonRetail). Detailed definitions of all variables are included in Appendix B. Standard errors are clustered by firm and time of the day. ***, **, and * indicate statistical significance at two-sided 1%, 5%, and 10% levels, respectively.
Regression model: $Log(Retail)_{it} = \beta_0 + \beta_1 Outage_t + \beta_2 Log(NonRetail)_{it} + \epsilon_{it}$

Table A.2: Informed Trading or Liquidity Provision?

	Panel A: $IPT_{adj}[0,5]$			
	(1)	(2)	(3)	(4)
SUE	0.000516	0.0000667	0.000811	0.000418
	(0.00163)	(0.00182)	(0.00172)	(0.00184)
Log(Retail)	0.0136	0.0208		
	(0.0195)	(0.0281)		
SUE × Log(Retail)	0.000158	-0.000784		
	(0.00274)	(0.00230)		
Log(Nonretail)	-0.0269	-0.0475		
	(0.0253)	(0.0474)		
SUE × Log(Nonretail)	-0.00229	0.00426		
	(0.00275)	(0.00834)		
Retail OIB			-0.00103	-0.00129
			(0.00110)	(0.00133)
SUE ×Retail OIB			0.000568	0.000565
			(0.000905)	(0.00115)
Controls	No	Yes	No	Yes
Controls*SUE Decile	No	Yes	No	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Day-of-Week FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Observations	97077	97077	97077	97077
Adj.R2	0.0404	0.0461	0.0404	0.0461

	Panel B: RPD			
	(1)	(2)	(3)	(4)
Log(Retail)	-0.00297	-0.00755		
	(0.00275)	(0.00513)		
Log(Non-retail)	0.00156	0.0416		
	(0.00144)	(0.0339)		
Retail OIB			-0.0000313	0.00228
			(0.0000306)	(0.00153)
Time-of-day FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Observations	608911	608911	608911	608911
Adj.R2	0.0126	0.0240	0.0141	0.0326

This table presents results of regressions of $IPT_{adj}[0,5]$ (panel A) and RPD (panel B) on retail trading volume (column 1) and order imbalance (column 2). Standard errors are clustered by firm and time-of-day. ***, **, and * indicate statistical significance at two-sided 1%, 5%, and 10% levels, respectively.

Regression model: $IPT[0,5]_{it} = \beta_0 + \beta_1 SUE_{it} + \beta_2 Retail_{it} + \beta_3 SUE_{it} * Retail_{it} + \sum \beta_k X_{k,it} + \sum \beta_k SUE_{it} * X_{k,it} + \epsilon_{it}$

$RPD_{it} = \beta_0 + \beta_1 Retail_t + \sum \beta_k X_{k,it} + \epsilon_{it}$

Table A.3: Retail trading matched to various post-earnings announcement windows

	BHAR[0,1]	*BHAR[2,5]*	*BHAR[2,22]*	*BHAR[2,45]*	*BHAR[2,next]*
	(1)	(2)	(3)	(4)	(5)
SUE	0.170***	0.120***	0.0179***	0.00398	0.0303***
	(0.00676)	(0.00655)	(0.00434)	(0.00390)	(0.00599)
Log(Retail)[0,1]	-0.148***				
	(0.0416)				
SUE × Log(Retail)[0,1]	0.0924***				
	(0.0151)				
Log(NonRetail)[0,1]	0.141**				
	(0.0538)				
SUE × Log(NonRetail)[0,1]	0.160***				
	(0.0180)				
Log(Retail)[2,5]		-0.193***			
		(0.0465)			
SUE × Log(Retail)[2,5]		0.0587***			
		(0.0153)			
Log(NonRetail)[2,5]		0.255***			
		(0.0717)			
SUE × Log(NonRetail)[2,5]		0.102***			
		(0.0195)			
Log(Retail)[2,22]			-0.00956		
			(0.0460)		
SUE × Log(Retail)[2,22]			0.0124		
			(0.0112)		
Log(NonRetail)[2,22]			0.0567		
			(0.0747)		
SUE × Log(NonRetail)[2,22]			0.00813		
			(0.0145)		
Log(Retail)[2,45]				-0.00799	
				(0.0485)	
SUE × Log(Retail)[2,45]				0.00771	
				(0.0110)	
Log(NonRetail)[2,45]				0.0679	
				(0.0842)	
SUE × Log(NonRetail)[2,45]				-0.00791	
				(0.0143)	
Log(Retail)[2,next]					-0.0791**
					(0.0392)
SUE × Log(Retail)[2,next]					-0.0185
					(0.0182)
Log(NonRetail)[2,next]					0.0663
					(0.0721)
SUE × Log(NonRetail)[2,next]					0.0274
					(0.0253)
Controls	Yes	Yes	Yes	Yes	Yes
Controls*SUE Decile	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes
Day-of-Week FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Observations	90707	90707	89565	86810	85304
Adj.R2	0.311	0.363	0.531	0.573	0.402

Notes: This table presents results of regressions of earnings announcement returns over different windows on earnings surprise quantiles interacted with Log(Retail) over different windows. All variables are standardized to be mean-zero and unit-variance. Control variables include PreRet, Log(Size), Book-to-Market, EVOL, EPersistence, ERepLag, #Estimates, TURN, Loss, #Announcements, IO, and Log(Nonretail). Controls are suppressed. Detailed definitions of all variables are included in Appendix B. Standard errors are clustered by firm and quarter. ***, **, and * indicate statistical significance at two-sided 1%, 5%, and 10% levels, respectively.
Regression model: $BHAR[a,b]_{it} = \beta_0 + \beta_1 SUE_{it} + \beta_2 Log(Retail)[a,b]_{it} + \beta_3 SUE_{it} * Log(Retail)[a,b]_{it} + \sum \beta_k X_{k,it} + \sum \beta_k SUE_{it} * X_{k,it} + \epsilon_{it}$

Table A.4: Earnings Announcement Returns, Post-earnings Announcement Drift, and Retail Trading (Extreme SUE)

	BHAR[0,1]	*BHAR[2,5]*	*BHAR[2,22]*	*BHAR[2,45]*	*BHAR[2,next]*
	(1)	(2)	(3)	(4)	(5)
SUE	0.155***	0.0981***	0.0112*	0.00542	0.0203***
	(0.00745)	(0.00781)	(0.00573)	(0.00549)	(0.00710)
Log(Retail)	-0.0595*	-0.0594*	-0.0149	0.0162	-0.0355
	(0.0318)	(0.0299)	(0.0289)	(0.0242)	(0.0255)
SUE × Log(Retail)	0.0794***	0.0434***	0.0210**	0.0228**	0.0210
	(0.0154)	(0.0152)	(0.00947)	(0.0113)	(0.0128)
Log(Nonretail)	0.144***	0.127***	0.0785	0.0341	0.0619
	(0.0467)	(0.0471)	(0.0490)	(0.0419)	(0.0404)
SUE × Log(Nonretail)	0.131***	0.0895***	0.00959	-0.00701	0.00952
	(0.0180)	(0.0179)	(0.0133)	(0.0169)	(0.0156)
PreRet	0.123***	0.0824***	-0.00690	0.000375	0.00381
	(0.0153)	(0.0143)	(0.0118)	(0.00913)	(0.0110)
Controls	Yes	Yes	Yes	Yes	Yes
Controls*SUE Decile	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes
Day-of-Week FE	Yes	Yes	Yes	Yes	Yes
Observations	33637	33637	33637	33637	33637
Adj.R2	0.348	0.399	0.574	0.606	0.391

Notes: This table presents results of regressions of earnings announcement returns over different windows on earnings surprise quantiles interacted with Log(Retail). This subsample include earnings announcements in extreme SUE deciles (1,2,10, and 11). All variables are standardized to be mean-zero and unit-variance. Control variables include PreRet, Log(Size), Book-to-Market, EVOL, EPersistence, ERepLag, #Estimates, TURN, Loss, #Announcements, IO, and Log(Nonretail). Detailed definitions of all variables are included in Appendix B. Standard errors are clustered by firm and quarter. ***, **, and * indicate statistical significance at two-sided 1%, 5%, and 10% levels, respectively.
Regression model: $BHAR[a,b]_{it} = \beta_0 + \beta_1 SUE_{it} + \beta_2 Log(Retail)_{it} + \beta_3 SUE_{it} * Log(Retail)_{it} + \sum \beta_k X_{k,it} + \sum \beta_k SUE_{it} * X_{k,it} + \epsilon_{it}$

Table A.5: Earnings Announcement Returns, Post-earnings Announcement Drift, and Retail Trading (Stocks with Penny Spreads)

	BHAR[0,1]	*BHAR[2,5]*	*BHAR[2,22]*	*BHAR[2,45]*	*BHAR[2,next]*
	(1)	(2)	(3)	(4)	(5)
SUE	0.0700***	0.0511***	-0.0209	-0.0415***	-0.0194
	(0.0199)	(0.0173)	(0.0147)	(0.0144)	(0.0252)
Log(Retail)	-0.412***	-0.299***	-0.162*	-0.111	-0.255**
	(0.0983)	(0.0939)	(0.0907)	(0.0838)	(0.105)
SUE × Log(Retail)	0.186***	0.0756*	-0.0124	0.0154	0.0184
	(0.0496)	(0.0412)	(0.0300)	(0.0354)	(0.0438)
Log(Nonretail)	0.353***	0.235*	0.203*	0.182**	0.249*
	(0.124)	(0.125)	(0.102)	(0.0851)	(0.137)
SUE × Log(Nonretail)	0.106*	0.105*	0.0711*	0.0335	-0.00371
	(0.0538)	(0.0521)	(0.0416)	(0.0430)	(0.0499)
PreRet	0.0832***	0.0388**	-0.0249	-0.0130	-0.0214
	(0.0199)	(0.0189)	(0.0182)	(0.0171)	(0.0151)
Controls	Yes	Yes	Yes	Yes	Yes
Controls*SUE Decile	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes
Day-of-Week FE	Yes	Yes	Yes	Yes	Yes
Observations	9540	9540	9540	9540	9540
Adj.R2	0.297	0.349	0.484	0.532	0.390

Notes: This table presents results of regressions of earnings announcement returns over different windows on earnings surprise quantiles interacted with Log(Retail). This subsample include stocks with bid-ask spreads below a penny on earnings announcement days. Bid-ask spread is the average time-weighted quoted bid-ask spread prior to trading. All variables are standardized to be mean-zero and unit-variance. Control variables include PreRet, Log(Size), Book-to-Market, EVOL, EPersistence, ERepLag, #Estimates, TURN, Loss, #Announcements, IO, and Log(Nonretail). Detailed definitions of all variables are included in Appendix B. Standard errors are clustered by firm and quarter. ***, **, and * indicate statistical significance at two-sided 1%, 5%, and 10% levels, respectively.
Regression model: $BHAR[a,b]_{it} = \beta_0 + \beta_1 SUE_{it} + \beta_2 Log(Retail)_{it} + \beta_3 SUE_{it} * Log(Retail)_{it} + \sum \beta_k X_{k,it} + \sum \beta_k SUE_{it} * X_{k,it} + \epsilon_{it}$

Table A.6: Earnings Announcement Returns, Post-earnings Announcement Drift, and Retail Trading (Size Split)

	BHAR[0,1]		*BHAR[2,5]*		*BHAR[2,22]*		*BHAR[2,45]*		*BHAR[2,next]*	
	Small	Big	Small	Big	Small	Big	Small	Big	Small	Big
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
SUE	0.203***	0.164***	0.134***	0.135***	0.0106	0.00407	-0.00667	-0.00660	0.00274	0.00621
	(0.0125)	(0.0140)	(0.0111)	(0.0129)	(0.00957)	(0.00971)	(0.00863)	(0.0120)	(0.0112)	(0.0203)
Log(Retail)	-0.0775***	-0.174***	-0.0750***	-0.149***	-0.0311	-0.0339	-0.00107	-0.0151	-0.0458**	-0.0525
	(0.0284)	(0.0580)	(0.0256)	(0.0538)	(0.0230)	(0.0474)	(0.0184)	(0.0345)	(0.0222)	(0.0451)
SUE × Log(Retail)	0.0734***	0.175***	0.0426***	0.131***	0.0154	0.0266	0.0141	0.0151	0.0120	0.0480
	(0.0134)	(0.0279)	(0.0135)	(0.0261)	(0.0102)	(0.0216)	(0.00934)	(0.0226)	(0.0106)	(0.0336)
Log(Nonretail)	0.118***	0.1000	0.121**	0.0960	0.0813**	0.0659	0.0403	0.0521	0.0579*	-0.00894
	(0.0430)	(0.0746)	(0.0450)	(0.0771)	(0.0377)	(0.0635)	(0.0253)	(0.0453)	(0.0343)	(0.0755)
SUE × Log(Nonretail)	0.129***	0.257***	0.0867***	0.114***	0.0114	0.0466	0.000212	0.0104	0.0230	0.0310
	(0.0194)	(0.0447)	(0.0180)	(0.0418)	(0.0149)	(0.0313)	(0.0138)	(0.0317)	(0.0152)	(0.0528)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls*SUE Decile	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	43799	53278	43799	53278	43799	53278	43799	53278	43799	53278
Adj.R2	0.351	0.313	0.416	0.359	0.595	0.532	0.631	0.588	0.367	0.440
	Difference in SUE × Log(Retail) coefficients									
	-0.0360		-0.0884		-0.0112		-.00105		-0.0360	
	(-0.0284)		(-0.0280)		(-0.0235)		(-0.0242)		(-0.0358)	

Notes: This table presents results of regressions of earnings announcement returns over different windows on earnings surprise quantiles interacted with Log(Retail). The sample split is based on firm size. All independent variables are standardized to be mean-zero and unit-variance. Control variables (suppressed) include PreRet, Log(Size), Book-to-Market, EVOL, EPersistence, ERepLag, #Estimates, TURN, Loss, #Announcements, IO, and Log(Nonretail). Detailed definitions of all variables are included in Appendix B. Standard errors are clustered by firm and quarter. ***, **, and * indicate statistical significance at two-sided 1%, 5%, and 10% levels, respectively. Statistical significance for differences in coefficients across subsamples is evaluated based on the standard errors of the coefficient on the interaction of SUE × Log(Retail) $\times 1_{right}$ where 1_{right} is an indicator for the right subsample condition, in a fully interacted specification, i.e., we allow each variable, including the fixed effects, to vary by the partitioning variable and drop observations that do not fall into either partition if relevant.
Regression model: $BHAR[a,b]_{it} = \beta_0 + \beta_1 SUE_{it} + \beta_2 Log(Retail)_{it} + \beta_3 SUE_{it} * Log(Retail)_{it} + \sum \beta_k X_{k,it} + \sum \beta_k SUE_{it} * X_{k,it} + \epsilon_{it}$

Table A.7: Earnings Announcement Returns, Post-earnings Announcement Drift, and Retail Trading (Concurrent EAs Split)

	BHAR[0,1]		*BHAR[2,5]*		*BHAR[2,22]*		*BHAR[2,45]*		*BHAR[2,next]*	
	Normal	Busy	Normal	Busy	Normal	Busy	Normal	Busy	Normal	Busy
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
SUE	0.172***	0.176***	0.115***	0.108***	0.0122**	0.0124*	0.00413	-0.00322	0.0244	0.0211
	(0.00729)	(0.00947)	(0.00615)	(0.00813)	(0.00547)	(0.00703)	(0.00492)	(0.00791)	(0.0266)	(0.0203)
Log(Retail)	-0.134***	-0.101***	-0.109***	-0.106***	-0.0151	-0.0539*	0.00513	-0.00723	-0.0621*	-0.00761
	(0.0396)	(0.0343)	(0.0374)	(0.0277)	(0.0423)	(0.0287)	(0.0320)	(0.0273)	(0.0321)	(0.0289)
SUE × Log(Retail)	0.110***	0.0662***	0.0714***	0.0310**	0.0186	0.00485	0.0222	0.00191	-0.00214	0.0345*
	(0.0163)	(0.0154)	(0.0153)	(0.0144)	(0.0120)	(0.0115)	(0.0148)	(0.0113)	(0.0172)	(0.0191)
Log(Nonretail)	0.0811	0.128**	0.0883*	0.129***	0.0619	0.0766*	0.0396	0.0524	0.0420	0.0289
	(0.0517)	(0.0494)	(0.0517)	(0.0473)	(0.0541)	(0.0403)	(0.0449)	(0.0424)	(0.0476)	(0.0461)
SUE × Log(Nonretail)	0.156***	0.147***	0.0969***	0.102***	0.0297*	0.0173	-0.00503	0.00799	0.0677***	0.00381
	(0.0214)	(0.0225)	(0.0208)	(0.0196)	(0.0171)	(0.0168)	(0.0196)	(0.0192)	(0.0240)	(0.0248)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls*SUE Decile	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	66714	30363	66714	30363	66714	30363	66714	30363	66714	30363
Adj.R2	0.318	0.471	0.362	0.570	0.481	0.703	0.531	0.695	0.422	0.469
	Difference in SUE × Log(Retail) coefficients									
	0.0438**		0.0404**		0.0137		0.0202		-0.0366	
	(0.0218)		(0.0203)		(0.0184)		(0.0207)		(0.0250)	

Notes: This table presents results of regressions of earnings announcement returns over different windows on earnings surprise quantiles interacted with Log(Retail). The sample split is based on the number of concurrent earnings announcements. All independent variables are standardized to be mean-zero and unit-variance. Control variables (suppressed) include PreRet, Log(Size), Book-to-Market, EVOL, EPersistence, ERepLag, #Estimates, TURN, Loss, #Announcements, IO, and Log(Nonretail). Detailed definitions of all variables are included in Appendix B. Standard errors are clustered by firm and quarter. ***, **, and * indicate statistical significance at two-sided 1%, 5%, and 10% levels, respectively. Statistical significance for differences in coefficients across subsamples is evaluated based on the standard errors of the coefficient on the interaction of SUE × Log(Retail) $\times 1_{right}$ where 1_{right} is an indicator for the right subsample condition, in a fully interacted specification, i.e., we allow each variable, including the fixed effects, to vary by the partitioning variable and drop observations that do not fall into either partition if relevant.
Regression model: $BHAR[a,b]_{it} = \beta_0 + \beta_1 SUE_{it} + \beta_2 Log(Retail)_{it} + \beta_3 SUE_{it} * Log(Retail)_{it} + \sum \beta_k X_{k,it} + \sum \beta_k SUE_{it} * X_{k,it} + \epsilon_{it}$

Table A.8: Earnings Announcement Returns, Post-earnings Announcement Drift, and Retail Trading (Friday versus Other days)

	BHAR[0,1]		*BHAR[2,5]*		*BHAR[2,22]*		*BHAR[2,45]*		*BHAR[2,next]*	
	Other days	Friday	Other days	Friday	Other days	Friday	Other days	Friday	Other days	Friday
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
SUE	0.177***	0.0816	0.114***	0.0574	0.0129***	-0.0292	0.00426	-0.0689	0.0221***	-0.0266
	(0.00699)	(0.0880)	(0.00623)	(0.0911)	(0.00429)	(0.0722)	(0.00414)	(0.0654)	(0.00526)	(0.105)
Log(Retail)	-0.124***	-0.135**	-0.111***	-0.0793	-0.0317	0.0264	0.00142	0.0444	-0.0569**	-0.0251
	(0.0402)	(0.0647)	(0.0374)	(0.0652)	(0.0342)	(0.0873)	(0.0263)	(0.0909)	(0.0272)	(0.0619)
SUE × Log(Retail)	0.0854***	0.0144	0.0460***	0.0323	0.0186**	0.0156	0.0134	0.0299	0.00453	0.0380
	(0.0142)	(0.0528)	(0.0140)	(0.0537)	(0.00862)	(0.0485)	(0.0102)	(0.0456)	(0.0134)	(0.0568)
Log(Nonretail)	0.119**	0.140	0.120**	0.120	0.0744	0.0790	0.0453	-0.0114	0.0585	0.147
	(0.0509)	(0.0937)	(0.0520)	(0.0958)	(0.0472)	(0.110)	(0.0391)	(0.110)	(0.0440)	(0.0918)
SUE × Log(Nonretail)	0.157***	0.263***	0.107***	0.228***	0.0152	0.0643	0.00207	-0.0428	0.0423**	0.122
	(0.0172)	(0.0724)	(0.0170)	(0.0690)	(0.0119)	(0.0590)	(0.0133)	(0.0508)	(0.0186)	(0.0763)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls*SUE Decile	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	92584	4493	92584	4493	92584	4493	92584	4493	92584	4493
Adj.R2	0.310	0.374	0.361	0.396	0.534	0.521	0.573	0.581	0.387	0.428
	Difference in SUE × Log(Retail) coefficients									
	0.0710		0.0137		0.003		-0.0165		0.0073	
	(0.0547)		(0.0559)		(0.0461)		(-0.0415)		(0.0613)	

Notes: This table presents results of regressions of earnings announcement returns over different windows on earnings surprise quantiles interacted with Log(Retail). The sample split is based on the day when earnings are announced. All independent variables are standardized to be mean-zero and unit-variance. Control variables (suppressed) include PreRet, Log(Size), Book-to-Market, EVOL, EPersistence, ERepLag, #Estimates, TURN, Loss, #Announcements, IO, and Log(Nonretail). Detailed definitions of all variables are included in Appendix B. Standard errors are clustered by firm and quarter. ***, **, and * indicate statistical significance at two-sided 1%, 5%, and 10% levels, respectively. Statistical significance for differences in coefficients across subsamples is evaluated based on the standard errors of the coefficient on the interaction of SUE × Log(Retail) $\times 1_{right}$ where 1_{right} is an indicator for the right subsample condition, in a fully interacted specification, i.e., we allow each variable, including the fixed effects, to vary by the partitioning variable and drop observations that do not fall into either partition if relevant.

Regression model: $BHAR[a,b]_{it} = \beta_0 + \beta_1 SUE_{it} + \beta_2 Log(Retail)_{it} + \beta_3 SUE_{it} * Log(Retail)_{it} + \sum \beta_k X_{k,it} + \sum \beta_k SUE_{it} * X_{k,it} + \epsilon_{it}$

Table A.9: Earnings Surprises and Retail Trading Volume

	PreRet	
	(1)	(2)
PreRetail	0.231***	0.0645*
	(0.0506)	(0.0370)
PreRetail × SUE	0.0406**	0.0372**
	(0.0160)	(0.0161)
PreNonretail	-0.101*	0.404***
	(0.0557)	(0.0518)
PreNonretail × SUE	0.00276	0.00605
	(0.0159)	(0.0160)
SUE	0.165***	0.154***
	(0.00602)	(0.00600)
Controls	No	Yes
Year-Quarter FE	Yes	Yes
Day-of-Week FE	Yes	Yes
Firm FE	Yes	Yes
Observations	97077	97077
Adj.R2	0.123	0.140

This table presents results of earnings surprise deciles and PreRetail in the 10-day window before earnings announcements on contemporaneous returns. All independent variables are standardized to be mean-zero and unit-variance. Control variables include Log(Size), Book-to-Market , EVOL, EPersistence, ERepLag, #Estimates, TURN, Loss, #Announcements, IO, and PreNonretail. Detailed definitions of all variables are included in Appendix B. Standard errors and coefficients are clustered by firm and quarter. ***, **, and * indicate statistical significance at two-sided 1%, 5%, and 10% levels, respectively.
Regression model: $PreRet_{it} = \beta_0 + \beta_1 PreRetail_{it} + \beta_2 SUE_{it} + \beta_3 PreRetail_{it} * SUE_{it} + \sum \beta_k X_{k,it} + \epsilon_{it}$

Table A.10: Robustness Tests: ERC and Brokerage Outages

	BHAR[0,1]			
	Original Sample	*Entropy Balanced Sample*	*Randomized Outages*	using *#Complaints* as Outage
SUE	0.152***	0.150***	0.150***	0.158***
	(0.00888)	(0.0195)	(0.00884)	(0.00902)
Outage	0.126***	0.0481	-0.00147	0.00780*
	(0.0293)	(0.0306)	(0.0255)	(0.00400)
Outage × SUE	-0.0613**	-0.0690***	0.000940	-0.0136***
	(0.0286)	(0.0249)	(0.00270)	(0.00357)
Log(MktVol)	0.00412	-0.0380	0.00334	0.00302
	(0.0248)	(0.0541)	(0.02482)	(0.0248)
PreRet	0.109***	0.0857***	0.109***	0.109***
	(0.00764)	(0.0174)	(0.00760)	(0.00764)
Controls*SUE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Day-of-Week FE	Yes	Yes	Yes	Yes
Observations	31860	31860	31860	31860
Adj.R2	0.390	0.390	0.390	0.389

Notes: This table presents results of regressions of earnings announcement returns on earnings surprise quantiles interacted with broker outages. Column (1) reports results using the original sample. Column (2) reports results using an entropy balanced sample. This sample is balanced on the means and standard deviations of SUE quantiles and control variables. Column (3) reports means and standard deviations of coefficients from 1,000 regressions using randomized outage indicators. In each of these regressions, we assign a randomized outage indicator for each earnings announcement. All variables are standardized to be mean-zero and unit-variance. Control variables include Log(MktVol), PreRet, Log(Size), Book-to-Market, EVOL, EPersistence, ERepLag, #Estimates, TURN, Loss, #Announcements, IO. Detailed definitions of all variables are included in Appendix B. Standard errors are clustered by firm and quarter. ***, **, and * indicate statistical significance at two-sided 1%, 5%, and 10% levels, respectively.

Table A.11: Descriptive Statistics for Outage and Non-outage earnings announcements

	Outage=0			*Outage=1*			
	N	mean	sd	N	mean	sd	Diff
SUE(raw)	31053	-0.00	0.14	1274	-0.00	0.07	-0.001
SUE	31053	6.99	3.09	1274	7.03	3.08	0.031
BHAR[0,1]	31053	-0.03	0.11	1274	-0.04	0.11	-0.011
BHAR[2,5]	31053	-0.06	0.19	1274	-0.09	0.19	-0.025
BHAR[2,22]	31053	-0.73	1.23	1274	-0.88	1.22	-0.152
BHAR[2,45]	31053	-1.73	2.75	1274	-2.49	2.99	-0.757*
BHAR[2,next]	31053	-0.73	1.17	1274	-1.17	1.37	-0.438*
Log(Retail)	31053	14.40	2.23	1274	14.40	2.26	-0.008
Log(Nonretail)	31053	16.97	2.33	1274	16.97	2.38	-0.005
#Complaints	31053	29.65	106.57	1274	4908.24	6845.52	4,878.594***
PreRetail	31053	16.00	2.02	1274	16.14	2.12	0.133
PreNonretail	31053	18.65	2.20	1274	18.74	2.26	0.094
Log(MktVol)	31053	17.07	2.30	1274	17.06	2.35	-0.009
PreRet	31053	0.01	0.11	1274	-0.01	0.15	-0.019
Log(Size)	31053	7.48	1.99	1274	7.58	2.09	0.096
Book-to-Market	31053	0.54	0.80	1274	0.50	0.87	-0.036
EPersistence	31053	0.14	0.36	1274	0.16	0.37	0.024*
EVOL	31053	1.64	5.71	1262	1.45	4.10	-0.191
ERepLag	31053	37.13	12.43	1274	40.01	13.83	2.879
#Estimates	31053	8.50	6.68	1274	8.46	6.75	-0.041
TURN	31053	30.81	321.46	1274	27.32	45.97	-3.492
Loss	31053	0.37	0.48	1274	0.41	0.49	0.036
#Announcements	31053	143.36	94.24	1274	125.92	106.90	-17.441
IO	31053	0.71	0.25	1274	0.63	0.22	-0.078***

Notes: This table presents descriptive statistics for the sample. The subsample with $Outage$ = 0 contains earnings announcements that have no outage incident in the two-day announcement window. The sample with $Outage$ = 1 contains earnings announcements that have at least one outage incident in the two-day announcement window. Detailed definitions of all variables are included in Appendix B. ***, **, and * indicate statistical significance at two-sided 1%, 5%, and 10% levels, respectively.

B Variable definitions

Variable	Description
BHAR[s,t]	Size and book-to-market adjusted return cumulated from trading day s through day t relative to the earnings announcement date, calculated as $BHAR[s,t]_{i,q} = \prod_{d=s}^{t}(1+ret_{i,d}) - \prod_{d=s}^{t} t(1+ret_{p,d})$, where $ret_{i,d}$ is the daily stock return of firm i and $ret_{p,d}$ is the return on the size and book-to-market matching portfolio on day d. Source: CRSP.
SUE	Earnings surprise relative to analyst consensus forecasts deflated by quarter-end share price. Measured as an inter-quarter quantiles as in DellaVigna and Pollet (2009). Source: IBES, CRSP.
Outage	A dummy variable that takes a value of one if a aggregate retail brokerage outage complaints in the earnings-announcement window or a 5-minute trading interval is in the top quintile of complaints for that time window. Source: Downdetector.com, Eaton et al. (2022).
Log(Retail)	Log value of one plus dollar volume of shares traded by retail investors over the earnings announcement window. TAQ trades are identified as retail trades based on the Boehmer et al. (2021) approach. Source: TAQ.
Log(NonRetail)	Log value of one plus market volume less retail trading volume over the earnings announcement window. Source: TAQ.
# Complaints	Aggregate retail brokerage outage complaints in the earnings-announcement window or a 5-minute trading interval. Source: Downdetector.com, Eaton et al. (2022).
PreRetail	Pre-earnings announcement retail activity. Aggregate retail trading volume (scaled by market volume) for earnings announcement trading date -10 to -1 relative to announcement date 0. Source: TAQ.
PreRet	Pre-earnings announcement returns. Compound excess return over the size decile portfolio for earnings announcement trading date -10 to -1 relative to announcement date 0. Source: CRSP.
Size	Market value of equity on the earnings announcement date in \$M. Source: CRSP.
Book-to-Market	Book to market ratio at the end of quarter for which earnings are announced. Source: Compustat.
EPersistence	Earnings persistence based on AR(1) regression with at least 4, up to 16 quarterly earnings. Source: Compustat.
IO	Institutional ownership as a fraction of total shares outstanding. Values greater than 1 are set to 1. Source: WRDS SEC Analytics.
EVOL	Standard deviation of seasonally differenced quarterly earnings over the prior 16 (at least 4) quarters. Winsorized at 1st and 99th percentiles. Source: Compustat.
ERepLag	Days from quarter-end to earnings announcement. Source: Compustat.
#Estimates	Number of analysts making quarterly earnings forecasts. Source: IBES Summary File.

Variable definitions (continued)

Variable	Description
TURN	Average monthly turnover for the 12 months preceding the earnings announcement. Source: CRSP.
Loss	Indicator for negative earnings. Source: Compustat.
#Announcements	Number of concurrent earnings announcements. Source: IBES.
RPD	Relative price discovery for each 5-minute interval t during NYSE trading hours over the two-day window around an earnings announcement, calculated as $RPD = \frac{\log(1+ret_{5min})}{\log(1+ret_{2day})}$. Source: TAQ.
$IPT_{adj}[0,5]$	Adjusted intraperiod price timeliness measure, calculated as $IPT_{adj}[0,5] = \sum_{i=0}^{5}(1 - \frac{\lvert BHAR_5 - BHAR_i \rvert}{\lvert BHAR_5 \rvert})$. Adjusted IPT is an improvement over traditional measures of IPT as it penalizes over-reactions and reversals(Blankespoor et al., 2020). Source: CRSP, TAQ.
MktVol	Market volume during 2-day earnings announcement window in $M. Source: CRSP.
RetailOIB	Marketable retail order imbalance for each firm i over the two-day window around an earnings announcement, calculated as $RetailOIB_i = \frac{RetailBuy_i - RetailSell_i}{RetailBuy_i + RetailSell_i}$, where $RetailBuy_i$ ($RetailSell_i$) is dollar volume of shares bought (sold) by retail investors. Retail investors' directional trades are identified based on the Boehmer et al. (2021) approach. Source: TAQ.