Retail Investor Trading and Market Reactions to Earnings Announcements*

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Abstract

Retail traders can help or hinder the impounding of earnings information into price, but inferences are complicated because retail traders select when, where, and how much to trade. We use trade-level data and exploit retail brokerage outages to provide causal evidence on how retail investors affect the pricing of public earnings information. We find that retail trading is associated with stronger price responses to earnings news during the earnings announcement (EA) window and greater post-earnings announcement drift, but only the EA-window effect is robust to identification using plausibly exogenous outages. Outage-based results are stronger for earnings announcements expected to have high retail activity ex ante. Furthermore, retail buy-sell imbalance during EAs is not associated with price responses to earnings news, inconsistent with retail trade as informed per se. Overall, our evidence is consistent with a model in which retail trade, particularly when it is identifiable to market makers, facilitates liquidity provision to other traders around earnings announcements.

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.

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. We focus specifically on how retail activity affects the pricing of earnings news 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 begin by developing a stylized model, building on Glosten and Milgrom (1985) and Hu and Murphy (2023), that shows how variation in retail trade can affect other traders' transaction costs. The key feature is that, as in our data, the market maker can offer payment for order flow (PFOF) to attract identifiable retail trade. The market maker faces less adverse selection when transacting against identified retail traders, which, due to competition between market makers, pushes down transaction costs for other traders. We posit that lower transaction costs for these other, plausibly more sophisticated traders, can facilitate the impounding of fundamental signals, like earnings, into price.

Consistent with this takeaway from the model, our empirical evidence shows that during the EA window, 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, 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 beliefs 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 lower ERCs. This effect is stronger for earnings announcements predicted to garner high retail activity. However, outages are not significantly associated with heterogeneity in PEAD. Overall, this suggests a causal effect of retail trade on ERCs, and an association between retail trade and PEAD that may be driven by selection.[1]

There are other models and narratives that are consistent with aspects of our results. For instance, retail trade could enhance ERCs if retail investors are relatively informed. We find that retail order imbalance in the EA window is insignificantly associated with returns or ERCs, inconsistent with the interpretation of retail trade as informed. Instead, our evidence

[1] Kumar and Lee (2006) find that retail investors are more active in trading small firms, lower-priced firms, firms with lower institutional ownership, and high book-to-market (B/M) firms. Interestingly, these are the same categories of firms where the PEAD has traditionally been more pronounced. This could mean that the association between retail trading and PEAD might be driven, at least in part, by the types of firms that retail investors choose to trade, rather than the trading activity itself influencing PEAD.

favors a liquidity provision via noise trade interpretation, consistent with our model. Additional tests corroborate this interpretation: bid-ask spreads are higher and depths are lower for high expected retail trade stocks during brokerage outages. Furthermore, our PEAD results suggest that retail traders may select to trade on earnings surprises whose information is impounded into price over a long horizon, potentially because of greater information content or processing difficulty. Such selection may be due to underlying attention or overconfidence effects, which could generate noise trade.

We discuss related literature and theories in Section 2, but note here two 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.[2] Hirshleifer et al. (2008) conclude that PEAD is not caused by individual investors: individual investors are net buyers after both positive and negative earnings surprises, and their net trades are not associated with PEAD. This is consistent with our inference that retail trade may have a selection-based rather than a causal association with PEAD. Despite the similarities, our study differs in several important respects from Hirshleifer et al. (2008). First, our research questions are substantively different. We focus on how retail investor activity affects market responses to earnings announcements during the announcement window as well as 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 trade. We exploit these outages as exogenous increases to retail frictions that allow us to better identify the effects of retail trading per se. Fourth, while Hirshleifer et al. (2008) base their findings on a random sample of individual investors from a single brokerage firm, our sample consists of retail order flows sourced from an extensive set of retail

[2]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.

brokerages largely spanning the market. 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.

Second, Michels (2023) exploits data on Robinhood holdings to examine retail activity around earnings announcements.[3] However, Michels (2023) 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 during the earnings announcement window and the Boehmer et al. (2021) measure of retail trade to develop causal inferences and show that they generalize beyond Robinhood holdings per se.

Our study contributes to the understanding of retail traders' potential effects on market reactions to earnings news. We focus on earnings announcements because they are salient, pre-scheduled public information releases. Our results provide the most consistent support for a model in which retail traders provide liquidity allowing reactions to and incorporation of public information. Our pattern of results tends not to support simpler narratives in which retail traders' net effect is impounding noise into returns or pushing prices towards efficient incorporation of public information. Notably, this suggests a conceptualization of retail traders that depends on other aspects of the information environment and market microstructure including the availability of public information, transaction costs, and other traders' responses to retail trade.

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

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

et al. (2020)) have found substantial 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, which 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 the elimination of trading commissions at other large brokerages popular among retail traders (Osterland, 2019).[4]

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) 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

[4]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. See Nerdwallet's list at `https://www.nerdwallet.com/best/investing/free-stock-trading`. Even-Tov et al. (2022) provide empirical evidence on the implications of no-fee trading for retail investors.

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 provide 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.[5] 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. 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. Inspired by Eaton et al. (2022), we develop a predictive model for retail trade, further illustrating how outage effects fluctuate based on anticipated retail trading patterns.

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

[5] 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.

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 earnings response coefficients (ERCs) and post-earnings announcement drift (PEAD). ERCs capture the sensitivity of returns during the announcement window to the news contained in the earnings announcement, proxied by the earnings surprise. PEAD represents systematic trends in returns associated with earnings surprises following earnings announcements. To better understand mechanisms, we also examine: 1) relations between retail trade and proxies for liquidity including bid-ask spreads and depth measures; and 2) the association between retail order imbalance (i.e., directional trade) and returns.

There are several theories from prior literature that suggest various patterns for associations between retail trade and market reactions around earnings announcements. Briefly, retail traders could be: a) no different from other traders (e.g., Barberis et al., 1998); b) noise traders who move price away from fundamentals but can provide liquidity to or impose risk on other market participants (e.g., Black, 1986); c) usually inattentive traders whose trading around earnings reflects greater attention to earnings news (e.g., DellaVigna and Pollet, 2009; Hirshleifer et al., 2009; Diamond et al., 2016); d) overconfident traders who under-react to earnings news (e.g., Daniel et al., 1998); or e) relatively informed traders (e.g., Kaniel et al., 2012) who trade correctly in advance of earnings news. In the next section, we offer a theory specific to our setting, focusing on liquidity provision by retail traders in the presence of market makers who pay for order flow. While our evidence can support or reject these theories, none directly addresses a setting of retail traders who can be identified and offered payment for order flow, a key feature of our empirical setting. In the next section, we present a model captures this feature.

3 Stylized model

We build a stylized one-period model featuring retail traders, market makers, and informed traders. We show that an increase in identifiable retail trade (i.e., retail trade that receives price improvement) can lead to lower transaction costs for other, plausibly more sophisticated market participants. This can allow more information to be impounded into prices without requiring retail traders to be informed per se. Such information can include earnings-related news (e.g., Kim and Verrecchia, 1994), though an earnings announcement is not explicitly included in our microstructure-focused model. Supporting calculations are provided in Appendix C.

The model builds on Glosten and Milgrom (1985) and Hu and Murphy (2023), the latter of which incorporates market makers that pay for identifiable retail order flow. As in Glosten and Milgrom (1985), the fundamental equity value of a firm is stochastic, with a share having an equal probability of being worth $\upsilon_H = \upsilon_0 + \sigma > 0$ or $\upsilon_L = \upsilon_0 - \sigma > 0$. There is a set of informed traders who know the fundamental value of the firm and arrive at the public market with rate γ. Liquidity constraints limit each informed trader to transacting only one share at a time. That is, if $\upsilon = \upsilon_H$ (υ_L), then the informed trader submits a buy (sell) order. There are also uninformed retail traders who trade randomly, with an equal probability of purchasing or selling one share independent of the true value of a share. Retail traders arrive to the public market at a rate of ρ and submit their orders to the payment-for-order-flow (PFOF) 'market' at a rate of ω.[6]

As in Hu and Murphy (2023), we start by considering a competitive Public Market Maker (PMM) who does not engage in PFOF. From their perspective, the expected value of a share conditional on observing a buy order (and the ask price, p_A^{PMM}, being lower than υ_H), is $E[\upsilon|\text{buy}] = \upsilon_0 + \sigma\frac{\gamma}{\gamma+\rho}$. Similarly, the expected value conditional on a sell order is $E[\upsilon|\text{sell}] = \upsilon_0 - \sigma\frac{\gamma}{\gamma+\rho}$.

[6]In Hu and Murphy (2023), which uses δ and r to parameterize the probabilities of trade from the different parties on the market and PFOF venues, $\gamma = 1 - \delta$, $\rho = r\delta$ and $\omega = (1 - r)\delta$, such that $\omega = 1 - \gamma - \rho$, but we do not impose that constraint.

Competition implies a zero profit condition such that the bid and ask prices are, respectively: $p_A^{PMM} = E[v|\text{buy}]$ and $p_B^{PMM} = E[v|\text{sell}]$. The bid-ask spread is thus $S^{PMM} = p_A^{PMM} - p_B^{PMM} = 2\sigma\frac{\gamma}{\gamma+\rho}$. Note that unlike in Hu and Murphy (2023), an increase in retail trade directed to PFOF market makers, ω, will not affect the PMM's bid-ask spread. This happens because an increase in PFOF retail trade does not imply a decrease in on-exchange retail trade, as in Hu and Murphy (2023). In our empirical setting, we observe variation in PFOF retail trade, rather than variation in the share of retail trade routed to PFOF market makers versus PMMs, and we construct the model to capture this variation of interest specifically.

The internalizing market maker (IMM) takes the PFOF order flow and is active on the exchange.[7] As in Hu and Murphy (2023), assume the IMM incurs a net internalization cost of K, which includes the payment inherent in PFOF, any price improvement offered, and marginal costs of internalization, net of unmodeled benefits of observing retail order flow and/or economies of scale. The IMM's profit function is then:

$$\pi^{IMM} = \underbrace{((S^{PMM}/2 - Z) - K) \times \omega}_{\text{internalization profit}} - \underbrace{Z \times (\gamma + \rho)}_{\text{on-exchange loss}},$$

where Z is "the dollar amount that the competitive IMM undercuts the PMM half-spread" (Hu and Murphy, 2023, p. 13). Solving for the competitive condition with $\pi^{IMM} = 0$ yields $Z = \frac{\omega(S^{PMM}/2-K)}{\gamma+\rho+\omega}$. Given the definition of Z and recalling that $S^{PMM} = 2\sigma\frac{\gamma}{\gamma+\rho}$, we have the following ask and bid prices: $p_A^{IMM} = v_0 + \sigma\frac{\gamma}{\gamma+\rho+\omega} + \frac{\omega K}{\gamma+\rho+\omega}$ and $p_B^{IMM} = v_0 - \sigma\frac{\gamma}{\gamma+\rho+\omega} - \frac{\omega K}{\gamma+\rho+\omega}$. Thus, the spread is $S^{IMM} = p_A^{IMM} - p_B^{IMM} = 2\frac{\sigma\gamma+K\omega}{\gamma+\rho+\omega}$. Note that IMM and PMM spreads

[7] In a competitive setting, the IMM's zero-profit condition implies that profitable trades against PFOF retail trade will subsidize loss-making trades on the exchange. Note that a zero-profit condition can be easily replaced with a positive-profit constraint (e.g., a positive contribution margin to cover fixed costs or the required return on capital), which would allow for the IMM's on-exchange trades to be profitable, but due to the PFOF subsidy, less profitable than the PMM's on exchange trades would be in the absence of PFOF. If the IMM's on-exchange trades are less profitable because lower spreads are charged, this could drive out the PMM (though positive search costs could allow for both IMM and PMM to be active while charging different spreads). Nonetheless, the analysis can be viewed as representing a setting in which the IMM competes with other unmodeled IMMs. The PMM spreads serve as a benchmark for comparison, and do not need to imply the PMM and IMM compete directly in market making for a given firm's stock.

converge as the retail order flow to the IMM goes to zero: $\lim_{\omega \to 0} S^{IMM} = S^{PMM}$.

The effect of an increase in PFOF retail trade, ω, on the IMM's on-exchange pricing (i.e., spread), is $\frac{dS^{IMM}}{d\omega} = 2\frac{K(\gamma+\rho)-\sigma\gamma}{(\gamma+\rho+\omega)^2} < 0$, where the final inequality is a consequence of $Z > 0$. This comparative static means that trading costs, S^{IMM}, faced by traders in other venues (e.g., informed traders on-exchange or in dark pools that also feature adverse selection) are decreasing in in PFOF retail trade, ω. In essence, identifiable PFOF retail trade subsidizes trading in other venues where informed traders participate. Linking this to earnings information is straightforward: lower trading costs for informed and other sophisticated traders can facilitate the impounding of earnings information into price (e.g., Gârleanu and Pedersen, 2013; Kim and Verrecchia, 1994).

4 Sample and variables

4.1 Earnings announcements sample

The sample consists of quarterly earnings announcements for U.S. common stocks, at the intersection of the TAQ, CRSP, Compustat, and IBES databases, from January 2010 to December 2021. We select this period due to the widespread adoption of internalization and price improvement practices for retail investors by brokerage firms and wholesalers by 2010 (Boehmer et al., 2021).

We detail our sample selection process in Table 1. We start with announcements available in Compustat and CRSP. The initial dataset is comprised of 139,870 firm-quarter earnings announcement (EA) observations. We exclude observations missing from the IBES database or those with multiple earnings timestamps within a single quarter, reducing the dataset to 131,966 firm-quarters. We further exclude announcements (firm-quarters) with missing returns, which results in a total of 82,031 firm-quarters.[8] Additionally, we exclude firms

[8]We retain only observations with stock returns available from 10 days before the EA through the next EA, to maintain a constant sample across specifications with different return windows. Observations where earnings are announced more than 100 days after the fiscal period end, and those with extremely high or

missing from TAQ (i.e., firms that were not listed on Nasdaq, NYSE, or AMEX), and those presenting multiple observations for the same ticker-date, bringing our total to 79,857 firm-quarters. Lastly, we eliminate observations with missing control variables. This leaves us with a sample of 65,321 unique earnings announcements from 3,979 unique firms.[9] Concise definitions of variables, discussed below, are provided in Appendix B.

We use earnings announcement dates from Compustat, provided they agree (to within 1 calendar day) with IBES-provided earnings announcement dates. Prior studies have shown a substantial number of earnings announcements occur outside market hours (e.g., Bochkay et al., 2020). For earnings released after 4 pm Eastern Time based on IBES timestamps, we adjust the earnings announcement date to the next trading day.[10]

4.2 Retail trading

Our methodology for measuring retail trading is based on Boehmer et al. (2021). We obtain transaction data from the daily TAQ database,[11] and identify trades as retail buys or sells in the TAQ data if they have an exchange code D and the trade was executed at a price just below (for buys) or above (for sales) a round penny.[12] Using the identified retail trades, we compute retail volume as follows:

$$\text{Retail Volume}_{it} = \text{Retail Buys}_{it} + \text{Retail Sales}_{it} \tag{1}$$

low estimated earnings persistence (abs(EPersistence) > 100) were also dropped.

[9] In our regressions, we drop an additional 127 singleton observations, i.e., observations where the fixed effects leave no identifying variation, yielding regression samples of 65,194 in our main panel analyses.

[10] 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.

[11] We follow the data cleansing steps described in Holden and Jacobsen (2014) for daily TAQ data.

[12] Trades with a tenth-of-a-cent digit between 0 and 4 (6 and 9) are classified as retail sales (buys). This classification reflects the price improvement relative to round penny prices favoring the seller (or buyer). Most market orders initiated by retail investors are either internalized by brokers or routed to wholesalers. These orders usually do not occur on registered exchanges and are recorded in TAQ with an exchange code D. Orders routed to wholesalers are typically filled at prices slightly better than the national best bid and offer, with price improvements usually less than a penny. Institutional investors are prohibited from receiving sub-penny price improvements by Regulation NMS.

Here, $Retail\ Buys_{it}$ and $Retail\ Sales_{it}$ represent buying and selling volumes initiated by individuals during interval t for stock i.[13] In our analyses, t refers to a one-day window on the adjusted earnings announcement day.

To address skewness, we use the natural log of $Retail\ Volume$ when employing it as a retail trade measure. We define nonretail trade as total market volume minus $Retail\ Volume$, and we control for the log of nonretail volume in our tests to help mitigate concerns that our retail volume measure simply acts as a proxy for overall trading volume.

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. The average quarterly % Retail Volume (Retail Volume scaled by total market 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 displays the retail and nonretail trading volume trends across a 60-day window surrounding earnings announcements. As in Figure 1, we present averages separately for small and large firms, based on market capitalization. In line with the findings from Figure 1, the average nonretail volume surpasses the retail volume in both subsamples, and this holds true for each day around the earnings announcement. Both small and large firms experience surges in both retail and nonretail volume, starting a few days before the earnings announcement and subsiding thereafter. Despite differences in the magnitudes (i.e., levels) across trade types and firm sizes, the time series patterns appear broadly similar.

[13] Retail trades identification follows Boehmer et al. (2021) and focuses on marketable retail orders. As documented by Kelley and Tetlock (2013), retail trade tends to be aggressive, and data from various retail brokerages confirm this. For instance, in their 2003-2007 sample, retail investors primarily submit market orders to meet their trading needs, with the number of retail market orders surpassing nonmarketable limit orders by over 35%.

4.3 Brokerage outages

Data regarding retail brokerage platform outages is obtained from Downdetector.com, compiled and kindly provided by the authors of Eaton et al. (2022). Downdetector.com tracks user-reported outages on websites broadly. In their work, Eaton et al. (2022) gathered data on outage complaints for various retail brokerages, including Charles Schwab, E-Trade, Fidelity, TD Ameritrade, and Robinhood, and monitored these at 5-minute intervals. We omit outages that are potentially misreported, excluding those with fewer than 200 outage complaints as per Eaton et al. (2022).

We construct an indicator, *Outage*, at the earnings announcement level. This indicator takes a value of one if the aggregate outage complaints during a firm's adjusted earnings announcement date belong to the top quintile of daily complaints (at least 526) in the timeframe encompassed by Eaton et al. (2022). To mitigate concerns about outages being driven by market-wide factors, we exclude outages experienced by all brokers simultaneously within the same 5-minute interval, following the approach suggested in Eaton et al. (2022).[14] In our analyses exploiting outages, we control for total market volume to prevent erroneous inferences that may arise from outages specifically driven by high-volume days.

4.4 Market reactions to earnings announcements and controls

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

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

where i represents the firm, t refers to the quarter, X_{it} denotes the actual earnings reported by IBES, $\mathbb{E}[X_{it}]$ represents the expected earnings, taken as the latest median forecast from

[14] While Eaton et al. (2022) examine the effect of different retail investor clienteles on stock market liquidity, our study concentrates on aggregate retail trading and its impact on the pricing of earnings news. As such, we do not conduct separate analyses for traditional brokers and Robinhood.

the IBES summary file, and P_{it} indicates the share price at the end of quarter t.[15] As in prior studies (e.g., DellaVigna and Pollet, 2009), when SUE acts as an independent variable, we use 11 SUE quantiles (five quintiles of negative surprises, five quintiles of positive surprises, and a no-surprise quantile at $SUE = 0$) based on calendar-quarter sorts.[16]

We compute daily excess returns each day as firm-specific returns after subtracting the returns on a size and book-to-market matched portfolio.[17] Earnings announcement returns used for earnings response coefficient (ERC) tests are computed as buy-and-hold excess (abnormal) returns from the earnings announcement day through the following day (a 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.

We use the following additional variables, mostly as controls, in line with previous literature (e.g., Hirshleifer et al., 2009): compound excess returns from ten to one day before the earnings announcement (PreRet); the natural logarithm of the market value of equity on the earnings announcement day (Log(Size)); the ratio of book value of equity to market value of equity at the quarter end (Book-to-Market); earnings persistence estimated based on quarter-to-quarter autocorrelation (EPersistence); institutional ownership represented as a fraction of total shares outstanding at the quarter end when the earnings are announced (IO); earnings volatility (EVOL); the reporting lag expressed as the number of days from quarter end to the earnings announcement (ERepLag); analyst following quantified as the

[15] Many variable definitions are similar to those in the earnings announcement sample in Andrei et al. (2023). The earnings surprise calculation follows the WRDS guidance as described in Dai (2020).

[16] Our main findings remain robust when using raw SUE (untabulated).

[17] We apply 25 matching portfolios based on the intersections of 5 portfolios formed on market capitalization and 5 portfolios created on book-to-market (i.e., independent sorts), following a similar method to that described at `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/tw_5_ports.html`. Portfolios are constructed annually and assigned to firms on June 30 according to firm size (market capitalization) and book-to-market ratios.

number of analysts making quarterly earnings forecasts according to the IBES summary file (# Estimates); average monthly share turnover over the previous 12 months (TURN); an indicator variable for negative earnings (Loss); and the number of other firms making earnings announcements on the same day (# Announcements).[18]

4.5 Liquidity measures

For our liquidity analysis, we use WRDS Millisecond Intraday Indicators measures based on TAQ, matched to the firm-EA day. The quoted spread is $\frac{ask-bid}{(ask+bid)/2}$, where the bid and ask values are captured at the market closing on the firm's EA day. For the effective spread, we use the dollar-weighted average percentage effective spread for trades during the firm's EA day. Percentage effective spread is defined at the trade level as $2 \times D \times \frac{P-M}{M}$, where P is the trade price, M is the midpoint of the bid-ask spread, and D is set to +1 for buy orders (where $P > M$) and -1 for sell orders (where $P < M$).[19]

Depth is the sum of time-weighted best bid and offer/ask share depths for each firm during trading hours on its EA day. We consider depth as an alternative liquidity measure because analyzing both spreads and depths together provides a better picture of variation in liquidity (Lee et al., 1993). Our liquidity measures are winsorized at the first and 99th percentiles.

4.6 Descriptive statistics and correlations

Descriptive statistics are provided in Table 2. Raw earnings surprises are on average near zero, but with wide dispersion, indicating wide variability in earnings surprises across different firms and quarters. Our quantile-based SUE measure addresses the dispersion and

[18] 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.

[19] The term "percent" in percent effective spread indicates that the effective spread is normalized by the midpoint of the bid-ask spread, facilitating comparison across firms with varying stock prices. WRDS computes the average of these percent effective spreads for each firm-day, weighting each trade's spread by its dollar value. The effective spread, which incorporates actual trade prices, indicates that liquidity providers may execute trades at prices within the quoted bid-ask spread (Petersen and Fialkowski, 1994).

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 buy-and-hold abnormal returns (BHAR) over the various windows examined are also close zero.

The average log-transformed retail and non-retail trading volumes during the announcement period (Log(Retail) and Log(Nonretail)) are approximately 14 and 17, respectively. These numbers suggest that non-retail trading volumes tend to be higher than retail volumes on average during the announcement window, consistent with Figure 2. Most earnings announcements are made on days with no complaints about retail brokerage outages on Downdetector.com, though the distribution of complaints is unsurprisingly right-skewed.

Table 3 shows raw pairwise correlations. The earnings surprise quantile, SUE, is positively and significantly correlated with abnormal returns in all relevant windows. SUE and announcement-window returns are also both strongly associated with the volume attributable to retail investors and non-retail investors. 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.

5 Results

We first present tests relating retail trading activity to price responses to earnings surprises, i.e., ERCs. 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 ERCs and PEAD. We then examine whether outage effects vary with the amount of expected retail trade. Finally, we test the key mechanism identified in our stylized model (Section 3), whereby identifiable retail trade facilitates lower transaction costs for other traders. We present additional analyses in Section 6.

5.1 Earnings announcement returns and retail activity

To test to the association between retail trading and ERCs. We estimate the following regression at the firm-quarter level:

$$\begin{aligned}\text{BHAR}[0,1]_{it} = \beta_0 + \beta_1\text{SUE}_{it} + \beta_2\text{Log}(\text{Retail})_{it} + \beta_3\text{SUE}_{it} \times \text{Log}(\text{Retail})_{it} \\ + \sum \beta_I \text{X}_{I,it} + \sum \beta_k \text{SUE}_{it} \times \text{X}_{k,it} + \epsilon_{it}.\end{aligned} \tag{2}$$

In equation (2), the dependent variable is the announcement-window abnormal stock return. $\text{Log}(\text{Retail})_{it}$ captures retail trading activity, and X_{it} is a set of controls, described in Section 4.4. The coefficient β_1 is an estimate of the average ERC. Our primary interest is the coefficient β_3 on SUE $\times$ $\text{Log}(\text{Retail})_{it}$, which captures the incremental effects of retail trade on the ERC. To simplify the interpretation of the non-interacted main effects and the economic magnitudes of interactions, all variables are standardized to have a mean of zero and a unit variance.

The coefficient estimates are presented in Table 4. Column 1 presents a specification without control variables, with the exception of year-quarter, day-of-week, and firm fixed effects. In this specification, the SUE coefficient is 0.366 ($p < 0.01$), implying a positive and both economically and statistically significant ERC. The coefficient on SUE $\times$ Log(Retail) is also positive and significant ($\beta = 0.266$, $p < 0.01$), suggesting a positive relation between retail trade activity and ERCs.[20]

Column 2 displays results for a specification including controls and their effects on ERCs, as represented by the interactions between each control and SUE. We regard this specification as more reliable because it facilitates the identification of the retail trade effect on ERCs, independent of potential confounding variables that can be included as controls (e.g., size,

[20] 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.

analyst coverage, prior turnover, and pre-EA returns). In this specification, the estimated average ERC is 0.313 ($p < 0.01$), and the coefficient of interest on SUE $\times$ Log(Retail) remains nearly unchanged in magnitude and significance ($\beta = 0.247$, $p < 0.01$).

Before continuing, we comment briefly on economic magnitudes. Focusing on the estimate in column 2 of Table 4, and recalling that variables are standardized to mean-zero and unit-variance, our estimate implies that a one standard deviation increase in Log(Retail) is related to an ERC that is higher by approximately 0.247. This signifies more than 75% of the average ERC of 0.313, a substantial economic implication. However, it is smaller than the estimated 0.317 increase in ERC from a standard-deviation increase in non-retail trading volume, Log(Nonretail). Notably, this could reflect the effect of retail trading on ERCs as well as a selection effect whereby investors trade more around more informative earnings announcements. We address this selection effect in subsequent tests below that exploit retail broker outages.

5.2 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 specifically on potential drift and reversal. This analysis is conducted based on estimates from equation (2), where the earnings announcement window returns (BHAR[0,1]) are substituted with post-earnings returns (BHAR[2,5], BHAR[2,22], BHAR[2,45], and BHAR[2,next EA]) as the dependent variable.

Table 5 presents our findings. For comparison, column 1 repeats the coefficients computed with BHAR[0,1] as the dependent variable, as shown in Table 4, column 2. The remaining columns depict estimates for post-announcement windows spanning one week, one month, two months, and through the next earnings announcement, respectively.

In line with prior studies finding a positive post-earnings announcement drift (e.g., Bernard and Thomas, 1990), we find that the coefficients on SUE in columns 2 through 5 are positive and significantly different from zero at the 1% level. Our key coefficients of interest, those on the SUE $\times$ Log(Retail) interaction, are consistently positive and significant ($p < 0.01$), with the exception of the coefficient in column 2 for BHAR[2,5] ($p > 0.10$). This implies that retail trading activity during the earnings announcement window is associated with positive drift in post-EA returns in the direction of the earnings surprise for periods extending beyond the week following the earnings announcement.

Our findings suggest that retail trading during the earnings announcement window positively affects post-earnings announcement returns over the months following the announcement. On its own, this is consistent with retail traders slowing the speed at which earnings information is impounded into price, i.e., by introducing dampening noise during the EA window that subsequently corrects. Retail traders as this kind of noise traders, however, is inconsistent with the positive association between retail trade and ERCs in Table 4. A concern is that retail trade may be endogenously higher for earnings that both provide more information to the market (leading to higher ERCs) and take longer to process (leading to higher PEAD). This is effectively a selection problem that has the potential to bias coefficient estimates. Below, we exploit brokerage outages to generate plausibly exogenous variation in retail trade less susceptible to such selection effects.

Before proceeding to the outage-based analysis, we discuss two interesting patterns evident in Table 5. First, average PEAD spikes in the [2,22] window at 0.206, relaxing to roughly 0.020-0.025 in months 2 and 3 following the EA. Similarly, the coefficient on the SUE $\times$ Log(Retail) interaction is estimated to be 0.202 for the [2,22] window but only 0.051 (0.027) over the two-month (three-month) windows. These suggest reversal, both overall and related to EA-window retail trade, in the 2nd month after the EA.

Second, the coefficients on the SUE $\times$ Log(Nonretail) interaction in columns 4 and 5 are significantly negative. Non-retail trade in the EA window thus appears to be associated with return reversals over the two- and three-month horizons. While retail trade contributes consistently to PEAD, the implications of non-retail trade on PEAD depend on the time horizon examined. As our focus is on retail trade, and our empirical strategy below allows us only to obtain plausibly exogenous variation in retail trade, we leave the non-retail volume-PEAD association as a potentially interesting focus for future research.

Building on the patterns in Table 5, Table 6 presents regressions specified as in (2), but with the dependent variable replaced with BHAR over non-overlapping windows from 6 days after the EA through the next EA. Estimating these regressions allows us to test for drift and reversal over the [6,22] (weeks 2 through 4), [23,45] (month 2) and [46,next EA] (month 3) windows. In column 1, we find that PEAD continues through the first month after the EA, with a coefficient on SUE of 0.211 ($p < 0.01$). Coefficients on interactions between SUE and both retail and non-retail trade are also positive, suggesting that EA volume in general is associated with one-month drift. The return pattern turns to reversal in the 2nd month after the EA, however, with a coefficient on SUE of -0.185 ($p < 0.01$). Similarly, the interaction coefficients with SUE and both retail and non-retail trade in column (2) are negative, implying that greater EA window trade is associated with stronger post-earnings announcement *reversals* two months after the EA. In the third month, captured in column (3), we observe a small but significant ($\beta = 0.02$, $p < 0.01$) PEAD coefficient on SUE, but insignificant coefficients on the SUE interactions with trading volumes. These patterns, to our knowledge, are novel to the PEAD literature, and deserve further investigation. Given our focus is on the effects of retail trade, and that selection to trade in and around earnings announcements is a major concern, we proceed to tests using brokerage outages as shocks to retail trade. The exogeneity of brokerage outages makes these tests plausibly less susceptible to the selection effects noted above.

5.3 Earnings announcement returns and retail frictions from platform outages

Our results thus far suggest that retail traders play a crucial role in incorporating publicly available earnings information into stock prices during the EA window, while, perhaps surprisingly, facilitating return drift following the announcement (i.e., PEAD). However, retail trading—and trading in general—is endogenous to the earnings response setting, as investors, including retail investors, can choose whether and how much to trade based on information about earnings, stock prices, and other signals 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 tease out more causal evidence, we capitalize on randomly timed outages experienced by retail brokerages. These outages, which substantially impede trading on the affected platforms, introduce an exogenous source of variation in retail trading frictions. Importantly, these frictions are plausibly independent of any given firm's earnings announcement and its informational content. To verify the negative effect of outages on retail volume, we estimate the following regression:

$$\text{Log(Retail)}_{it} = \beta_0 + \beta_1 \text{Outage}_t + \sum \beta_k \text{X}_{it} + \epsilon_{it} \tag{3}$$

where Log(Retail)_{it} is the retail trading volume during 5-minute interval t for stock i. Outage is an indicator for top-quintile complaints during a 5-minute interval, and the controls vector, X, includes firm and time-of-day fixed effects and firm-time non-retail trade. We estimate equation (3) on a sample including 5-minute 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 in the Appendix presents our estimates of equation (3). We find that outages are negatively associated with retail volume, as expected, and in line with Barber et al. (2021) and Eaton et al. (2022).

Having demonstrated a negative association between outages and retail trade, we exploit outages as shocks whose timing is random with respect to earnings announcements. This allows us to provide plausibly causal evidence on the effects of retail trading on market reactions to earnings information. We show in Table A.2 in the Appendix that earnings announced on days with significant outages are broadly similar to earnings announced on other days, consistent with random assignment with respect to SUE, returns, and trading activity. We estimate specifications similar to (2), replacing Log(Retail) with a proxy for significant brokerage outages:

$$\begin{aligned}\text{BHAR[a,b]}_{it} =&\beta_0 + \beta_1\text{Outage}_t + \beta_2\text{SUE}_{it} + \beta_3\text{SUE}_{it} \times \text{Outage}_t + \sum \beta_I \text{X}_{I,it} \\ &+ \sum \beta_k \text{SUE}_{it} \times \text{X}_{k,it} + \epsilon_{it}\end{aligned} \tag{4}$$

where $Outage_t$ is an indicator variable for 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,b], $b \in \{5, 22, 45, \text{next EA}\}$. We include the same fixed effects, controls, and controls interacted with SUE as in Table 5, 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. Table A.2 provides descriptive statistics for this subsample.

Results of estimating equation (4) are shown in Table 7. The ERC and PEAD coefficients in the first row follow a pattern similar to that in Table 5. Turning to the coefficient of interest on Outage × SUE, its estimate of -0.060 ($p < 0.05$) in column 1 implies that retail brokerage outages are associated with smaller ERCs. This implies a plausibly causal role of retail trading in shaping immediate market reactions to earnings announcements, consistent with the positive association between retail trade and ERCs shown in Table 4.

Results linking retail trading frictions to PEAD, however, are inconsistent with our association-based results. We do not find evidence of a statistically significant relationship between retail outages and incremental PEAD in column 2-5 of Table 7. This weakens our ability to infer a positive causal effect of EA retail trade on PEAD, as might be implied by the associative analysis presented in Table 5. As indicated above, selection effects may explain the difference in coefficient patterns. Although retail trade can have a causal positive effect on the impounding of earnings information during the EA window, EA retail trade may also be attracted to earnings announcements characterized by greater PEAD, e.g., due to properties of the information that is announced or trading frictions that slow the impounding of information. Since these are plausibly orthogonal to the timing of retail brokerage outages, their effects would not be captured by the Outage $\times$ SUE interaction coefficients in columns 2-5 of Table 7.

5.4 Analysis using outages and predicted retail trade

In this section, we provide additional evidence supporting our inferences from Table 7 by exploiting predictable heterogeneity in retail trade across earnings announcements. This aids identification and mitigates concerns of spurious inference from our outage analysis presented thus far, as retail brokerage outages are most likely to affect announcements where retail trade would have otherwise been more active. This also helps avoid concerns that outages capture variation in market-wide news or activity, which should have systematic effects rather than effects that vary with expected retail trade at the firm-day level.

Following Eaton et al. (2022), we examine the incremental effects of outages on stocks with high versus low expected retail activity, where expected retail activity is derived from a regression model. However, we modify their methodology to better align with our research context and empirical setting, given their focus on daily market quality and contrasting Robinhood to other retail investors and ours on reactions to earnings information for retail trading generally. First, we do not include WallStreetBets mentions as predictors. Such mentions, though salient for meme stocks and Robinhood trading, do not necessarily encapsulate the trading dynamics of the broader market around earnings announcements. Our emphasis is on comprehensively understanding retail trading spanning various platforms, beyond just Robinhood.[21] Second, we exclude the preceding overnight returns (i.e., close-to-

[21] Additionally, predictors based on WallStreetBets (WSB) are unnecessary for a high-powered predictive model. Most of the explanatory power in predicting retail volume in Eaton et al. (2022) comes from lagged retail trade, rather than their indicators for WSB quintiles. This can be seen by comparing the R^2 in

open) from our predictive model because they coincide with the period when earnings are typically announced. Their inclusion would inevitably overlap with our [0,1] close-to-close earnings announcement window returns, leading to potentially spurious estimates. Third, we focus on retail trading orthogonal to lagged return levels. Although Eaton et al. (2022) incorporate lagged returns in the day [-5,-2] and [-2,-1] windows as predictors, prior research (e.g., Ball and Brown, 1968; Baruch et al., 2017) demonstrates that pre-EA returns contain information about upcoming earnings surprises.[22] By orthogonalizing retail trade against pre-EA returns, we ensure our model remains uncontaminated by predictors that might inadvertently signal the magnitude of an impending earnings surprise. This precaution further shields our analysis from misleading correlations. Finally, we exclude date fixed effects from our predictive model, since these are collinear with date-level indicators for outages and could spuriously incorporate the effects of outages into our prediction model, which is supposed to predict retail trade *absent* outages.[23]

Specifically, we leverage a three-step methodology. We first isolate the component of retail trading volume that is orthogonal to recent returns. For this, we regress $Log(Retail)_{i,t}$ on returns in the [-5,-2] and [-2,-1] windows, $Return_{t-2\ to\ t-1}$ and $Return_{t-5\ to\ t-2}$.[24] We estimate the following regression for all firm-days:

$$\text{Log(Retail)}_{i,t} = \beta_0 + \beta_1 \text{Return}_{t-2\ to\ t-1} + \beta_2 \text{Return}_{t-5\ to\ t-2} + \epsilon_{i,t}. \tag{5}$$

the third and fourth columns of their Table 4, which rise from 0.24 to 0.86 with the inclusion of lagged retail trade (highly significant, t-stat = 106.6) and lagged Robinhood trade (insignificant, t-stat = -1.32). Additionally, the WSB variables alone explain less than 10% of the variation in retail order imbalance explained jointly by the WSB variables and controls (compare the third and fourth columns in Table 3). Second, one focus of Eaton et al. (2022) was specifically on Robinhood investors. As indicated by Barber et al. (2021), Robinhood investors display tendencies to herd into certain stocks, and are conjectured to be more significantly influenced by financial social media compared to other retail investors. WSB has more limited implications for aggregate retail trade, which is our focus.

[22]Regressions reported in a prior version of this paper also demonstrate that pre-EA returns contain information about the earnings surprise.

[23]Eaton et al. (2022) do not explicitly list firm and date fixed effects as included in their Table 4 prediction regressions, but their inclusion can be inferred from the replication package (available at `https://data.mendeley.com/datasets/5mjd8kbvbd/1`.

[24]We use these windows because they were included in the prediction model of Eaton et al. (2022).

From this regression, we extract the residuals, $\hat{\epsilon}_{i,t}$, which capture variation in $Log(Retail)$ that is not explained by lagged returns. We then regress the residuals on the remaining predictors from Eaton et al. (2022), estimated at the stock-day level (i.e., not restricted to EA days):

$$\text{Residualized Log(Retail)}_{i,t} = \beta_0 + \lambda' \mathrm{X}_{i,t-1}^{firm} + \gamma \text{Log(Retail)}_{i,t-1} + \delta \text{Log(Mkt)}_{i,t-1} + \epsilon_{i,t}, \quad (6)$$

where Residualized $\text{Log(Retail)}_{i,t}$ is $\hat{\epsilon}_{i,t}$ from equation (5), $\mathrm{X}_{i,t-1}^{firm}$ is a vector of lagged firm-level control variables, and $Log(Retail)_{i,t-1}$ and $Log(Mkt)_{i,t-1}$ are lagged retail trading volume and lagged market-wide volume, respectively. We also include firm fixed effects. The fitted values from this regression represent our measure of expected orthogonal retail trading activity, which we denote as $E[Retail]$.

Table 9.A presents results from estimating equation (5). Both lagged return variables are positively associated with Log(Retail). This suggests that retail trading volume tends to increase following positive returns, consistent with retail trade on average following return momentum. Estimates of equation (6) are shown in Table 9.B. Retail trade, orthogonalized against recent lagged returns, is positively associated with the returns range, recent retail trade, and recent market volume, and negatively associated with return skewness. The adjusted R^2 is 0.874, implying a high degree of predictability for retail trading volume based on our predictors. This is comparable to the regression R^2 of 0.860 reported in the predictive model of Eaton et al. (2022, Table 4, column 4).

As in Eaton et al. (2022), we focus on differences between high and non-high expected retail trade, where high is defined as top-quintile. Specifically, we take $E[Retail]$ from the regression estimated in Table 9.B, drop non-EA days, sort into quintiles, and define $ERetail^{TQ}$ as an indicator for top-quintile $E[Retail]$ within EA days. Interacting this indicator with the variables of interest from equation (4) yields an approach similar to a difference-in-differences design. The estimate of interest in this analysis involves, first, the difference in

ERCs and PEAD for firms with retail brokerage outages on EA days versus those without, and, second, the difference across firms with high versus low expected retail trade. If retail trade is causally associated with higher ERCs, we expect to see incrementally lower ERCs for announcements on outage days for firms with high expected retail trade. Specifically, we estimate the following regression equation:

$$\begin{aligned}\text{BHAR[a,b]}_{it} = \beta_0 &+ \beta_1 \text{Outage}_t + \beta_2 \text{SUE}_{it} + \beta_3 ERetail^{TQ} + \beta_4 \text{SUE}_{it} \times \text{Outage}_t \\ &+ \beta_5 ERetail^{TQ} \times \text{Outage}_t + \beta_6 \text{SUE}_{it} \times ERetail^{TQ} \\ &+ \beta_7 \text{SUE}_{it} \times \text{Outage}_t \times ERetail^{TQ} \\ &+ \sum \beta_k \text{X}_{k,it} + \sum \beta_k \text{SUE}_{it} \times \text{X}_{k,it} + \epsilon_{it},\end{aligned} \tag{7}$$

where $ERetail^{TQ}$ is an indicator for top-quintile expected retail trading volume. Other variables are the same as in equation (4).

Table 9.C shows the incremental effects on ERCs and PEAD of brokerage outages on firms with high predicted retail trading activity. The coefficients of interest are on the triple interaction between SUE, Outage, and $ERetail^{TQ}$. In column 1, this coefficient is negative and significant ($\beta = -0.060$, $p < 0.05$). This implies that for firms with higher expected retail trading, the positive market reaction to earnings surprises is reduced during brokerage outages. This result confirms the plausibly causal role of retail trading in increasing EA-window price reactions to earnings news. In line with the results in Table 7, the coefficients of interest on the triple interactions in columns 2-4 are insignificantly different from zero, though there is a positive and marginally significant ($\beta = 0.050$, $p < 0.10$) coefficient for the [2,next EA] window. This is consistent the under-reaction related to the outage during the EA window for high expected retail trade announcements reversing around the subsequent EA. Additionally, we find a positive coefficient in column 1 on the SUE $\times$ $ERetail^{TQ}$ interaction, consistent with a positive association between high expected retail trade and ERCs, which could be driven by retail traders' selection to trade around more informative earnings.

Overall, our evidence presented thus far implies that EA-window retail trade increases market reactions to earnings news, resulting in higher ERCs. Associative evidence suggests that retail trade also facilitates PEAD, but this is not confirmed by a natural experiment exploiting retail brokerage outages.

5.5 Retail noise or informed trade: buy-sell imbalance tests

We next test whether the average direction of trade for retail investors during earnings announcements is associated with EA returns and ERCs, using retail order imbalance during the EA window defined as:

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

If retail trade is reacting to the EA, either in an informed or overconfident way, then we expect retail order imbalance to be positively associated with returns, and market reactions to earnings surprises to be stronger when the surprises are aligned with retail OIB. If retail trade is mostly noise, then retail OIB should be roughly independent from returns.[25] To distinguish these, we re-estimate our ERC regressions from Table 4 replacing log retail volume with Retail OIB as the independent variable of interest.

Table 10 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. This is further corroborated by Figure 3, which shows a similar pattern of retail buy-sell imbalance for both positive and negative earnings surprises. Except for a notable increase leading up to the earnings announcement,

[25] In many theoretical microstructure studies, building on Kyle (1985), market makers set stock prices based on expectations of fundamental value conditional on aggregate order flow. In such a setting, price is responsive to noise trade because the market maker cannot distinguish noise from informed trade. If they could, then price would be independent of noise trade. In our setting, and inherent in the Boehmer et al. (2021) identification of retail trade, market makers (i.e., wholesalers paying for order flow) *can* distinguish retail trade from other order flows. As such, in our setting retail-as-noise should yield effectively no association between net order flow (i.e., Retail OIB) and returns.

the retail buy-sell imbalance across the two series plotted in 3 is slightly negative.

The evidence presented in Table 10 and Figure 3 suggests that retail traders are not generally responding to the information in public earnings surprises. Instead, our findings indicate that the nature of retail order flow is more akin to noise trade, unrelated to fundamentals. This comports with wholesalers' practice of offering price improvements (i.e., payments for order flow) to largely noisy retail order flow (e.g., Easley et al., 1996).

5.6 Liquidity

Our stylized model in Section 3 predicts that an increase in PFOF retail trade allows market makers to offer more competitive (narrower) spreads on public exchanges. This lowers trading costs for informed or sophisticated traders, which allows the impounding of earnings news.

We test our model's trading cost prediction using a similar design as in Table 9.B, exploiting brokerage outages and high versus low expected retail trading.[26] Based on the model, we expect outages to be associated with higher spreads for stocks with high expected retail trading. Specifically, we estimate the following regression model:

$$\text{Liq}_{it} = \beta_0 + \beta_1 \text{Outage}_t + \beta_2 \text{ERetail}^{TQ} + \beta_3 \text{ERetail}^{TQ} \times \text{Outage}_t + \beta_4 \text{SUE}_{it} + \epsilon_{it},$$

where Liq_{it} is the quoted spread, effective spread, and depth for each stock i on EA day t. Although absent from our model per se, we examine depths because spreads alone are an incomplete proxy for trading costs (e.g., Lee et al., 1993). The variables Outage_t, ERetail^{TQ}, and SUE_{it} are defined as in equation (7).

Table 11 presents our results. The interaction term between Outage and ERetail^{TQ}, particularly in columns 1 and 2, shows positive and significant coefficients. This indicates that firms with high expected retail trading activity experience wider on-exchange spreads during brokerage outages, consistent with our model's predictions. Moreover, we observe

[26] Eaton et al. (2022) show that retail trade (besides that originating from Robinhood) is associated with lower on-exchange transaction costs, but do not focus on earnings announcements.

a significant reduction in depth (consistent with lower liquidity) among firms with high anticipated retail trade during these outages ($\beta = -207.0$, $p < 0.10$). In summary, our empirical analysis corroborates the theoretical prediction that identifiable PFOF retail trade is associated with lower trading costs in earnings announcement windows.

5.7 Overall inference

We view our evidence, overall, as consistent with a nuanced view of retail trade. Our best evidence, based on outages, with support from Retail OIB tests, suggests that retail trade around earnings announcements represents noise that facilitates higher ERCs, plausibly by providing liquidity that lowers other traders' trading costs. Our other evidence points to a positive (non-causal) association between retail trade and PEAD, consistent with a selection effect in which retail trade is more likely around earnings announcements that take more time to be incorporated into price. Although we use the term selection, retail traders selecting to trade in certain stocks could be driven by attention or overconfidence effects. Retail attention may be attracted to earnings that are difficult to predict and interpret, potentially because they are overconfident about their ability to profit in such an environment. Nonetheless, in the EA window, their trading seems to provide liquidity to traders who impound earnings news.

6 Additional analyses

This section discusses additional analyses, presented in Appendix A, that support our earlier analysis and show robustness to alternative specifications or sample cuts. Table A.1, discussed above, supports our use of outages as a negative shock to retail trade using intraday data. Table A.2 shows that earnings announced on outage and non-outage days are largely similar. Table A.3 presents PEAD regressions with EA-window retail trade replaced by PEAD-window retail trade, and finds results consistent with those in Table 5.

Tables A.4-A.9 replicate our ERC and PEAD regressions in subsamples and, in Tables A.6-A.9, compare the coefficients of interest across subsamples. Table A.4 limits the sample to extreme earnings announcements (top 2 and bottom 2 quantiles). Table A.5 uses a subsample with single-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).[27] Table A.6 presents estimates from subsamples of positive-only and negative-only SUE and shows that retail trade is associated with incrementally higher ERCs for positive earnings news. Consistent with this, Figure A.1 demonstrates that retail trading volumes (as well as non-retail volumes) tend to be higher around positive surprises compared to negative surprises. Table A.7 presents estimates split by firm size. Retail trade amplifies the ERC more in larger firms than in smaller firms. Table A.8 separates normal EA days from busy EA days, i.e., days without too many competing earnings announcements. Coefficients of interest are not significantly different across this split. Table A.9 shows that our result are similar for EAs falling on Fridays as for EAs falling on other days (e.g., DellaVigna and Pollet, 2009).

Table A.10 shows that our outage-based results are robust to entropy balancing to address potential differences between earnings announced on outage days versus non-outage days and to using the EA day's number of complaints in lieu of the top-quintile complaint indicators. 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 (repeated 1,000 times to generate coefficient distributions). Table A.11 shows that our inferences are insensitive to defining outage days based on other quantiles of the distribution of complaints.

[27] Barber et al. (2022) note the potential for signing errors due to fluctuating spreads, which could affect our OIB tests but are unlikely to affect our analysis of unsigned trade volumes.

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, which 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.

Our findings suggest that retail activity leads to stronger reactions to earnings announcements, which is consistent with information-based trade or liquidity provision. Furthermore, ERCs are lower for EAs which are affected by retail brokerage outages, and this effect is stronger for announcements expected to receive high retail trade. Retail traders potentially impound noise into prices, but can also trade on available information and provide liquidity to other market participants. Additional evidence aligns with liquidity provision, as retail order imbalance is not associated with EA window returns or their sensitivity to the earnings surprise. Furthermore, although we find a relation between retail activity and PEAD in associative tests, a lack of support in outage-based tests implies that selection effects may explain the association-based evidence. Specifically, retail traders may trade more around earnings announcements that take longer to impound into price. In spite of this, their liquidity provision during the EA window leads to stronger market reactions and ERCs.

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 (2023). Retail trade during the earnings announcement window is associated with higher PEAD, but not in tests exploiting a (lack of) retail trade exogenously driven by retail brokerage outages. Our inference is similar to Hirshleifer et al. (2008), in that we cannot reject the null hypothesis that retail trade has no causal effect on PEAD.

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. Prior studies have largely used data from periods in which internet-based stock market information was harder to access and trade on (e.g., the early to mid-1990s). Broadly, our results 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, potentially due to the multiple ways they can now access and trade on various signals (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., 2023), 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 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 one-dimensional noise traders seems warranted.

Figures

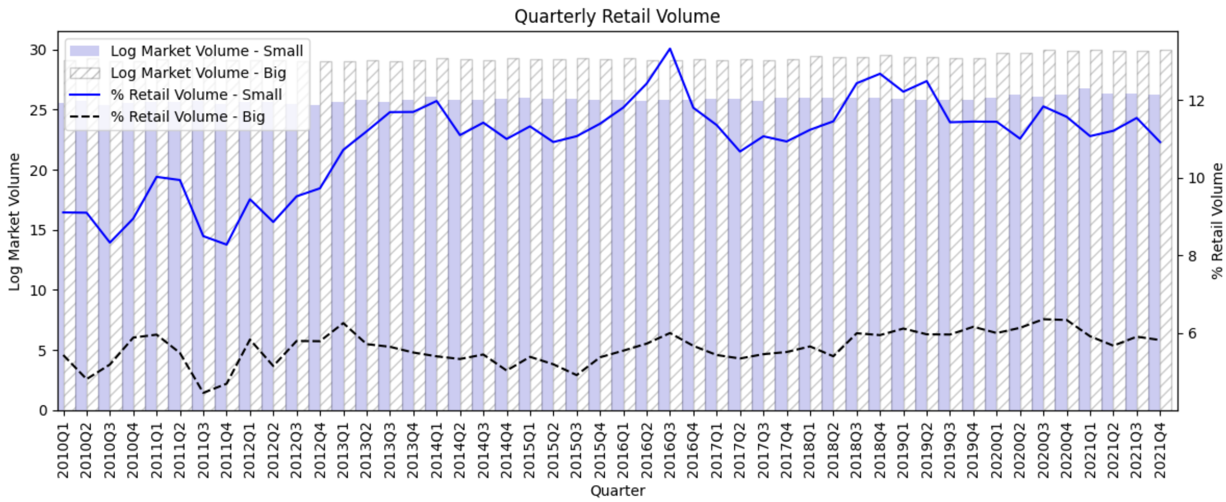

Figure 1: Quarterly Market Volume (dollar value traded) and % Retail Volume for small and big firm subsamples. Small and big designations are based on a median split on market value of equity.

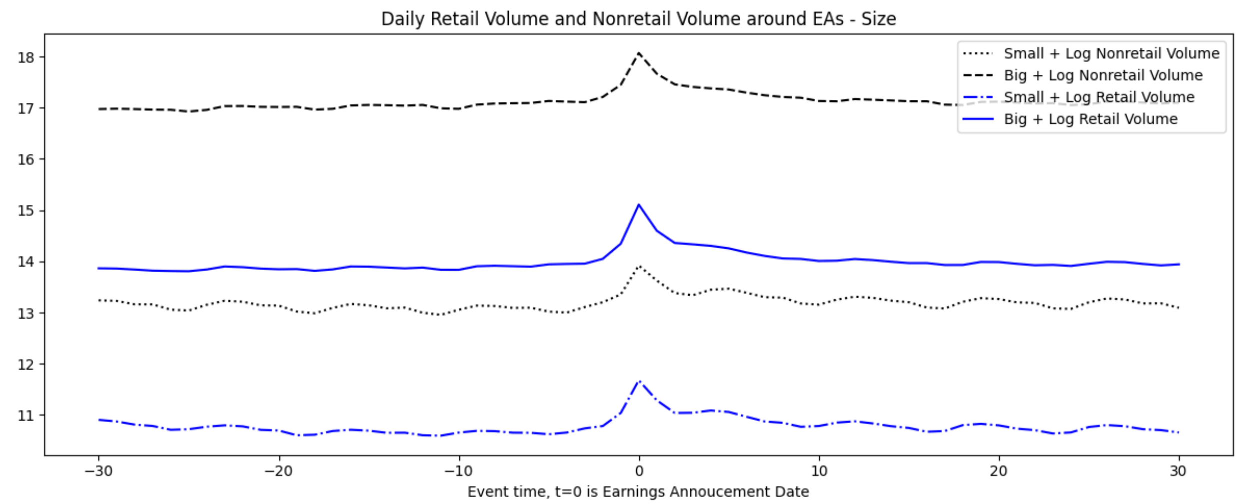

Figure 2: Daily Retail and Nonretail Volume around earnings announcements for small and big firm subsamples. Small and big designations are based on a median split on market value of equity.

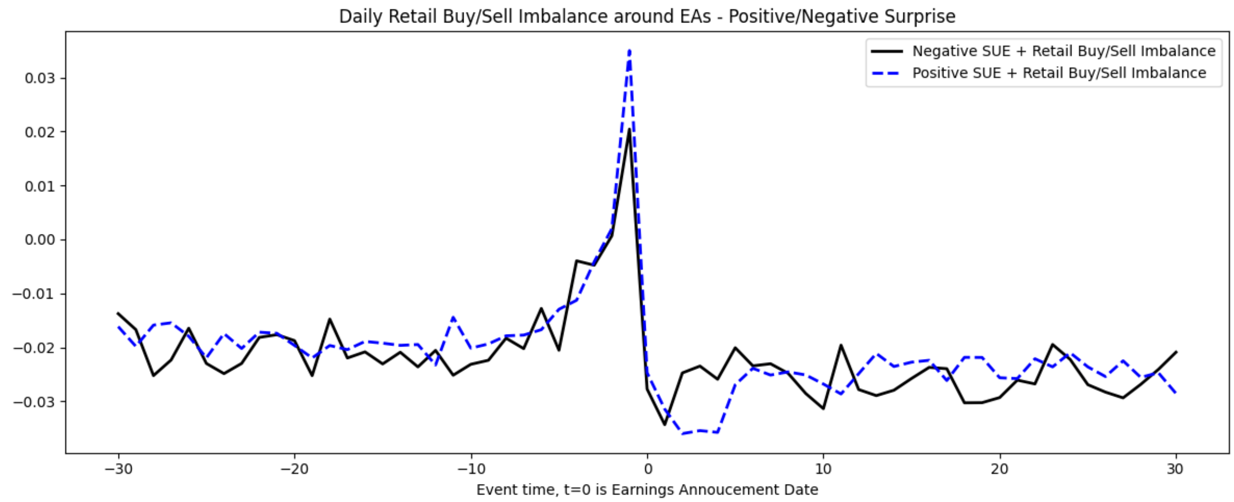

Figure 3: Daily Retail buy-sell imbalance around earnings announcements for positive and negative earnings surprises.

Tables

Table 1: Sample selection

	Earnings Announcements
Compustat and CRSP sample	139,870
Less: missing IBES data or with multiple earnings timestamps per quarter	7,904
Less: missing returns	49,935
Less: missing TAQ data, i.e., not listed on Nasdaq/NYSE/AMEX or with multiple ticker-date observations	2,174
Less: missing controls	14,536
	Final Sample
Unique firms	3,979
Unique earnings announcements	65,321

Table 2: Descriptive Statistics

	mean	sd	min	max	N
SUE(raw)	-0.00	0.07	-13.20	1.95	65321
SUE	6.91	3.18	1.00	11.00	65321
BHAR[0,1]	-0.00	0.08	-0.25	0.26	65321
BHAR[2,5]	-0.00	0.05	-0.15	0.18	65321
BHAR[2,22]	0.00	0.14	-0.37	0.50	65321
BHAR[2,45]	-0.00	0.15	-0.41	0.59	65321
BHAR[2,next]	-0.00	0.17	-0.47	0.69	65321
#Complaints	233.59	1500.54	0.00	12598.00	65321
Log(Retail)	14.49	1.98	5.99	21.85	65321
Log(Nonretail)	17.18	2.16	7.50	23.58	65321
Log(MktVol)	17.26	2.13	7.70	23.61	65321
PreRet	0.01	0.10	-0.79	2.22	65321
Log(Size)	7.15	1.78	0.89	13.56	65321
Book-to-Market	0.66	0.64	0.00	56.96	65321
EPersistence	0.15	0.34	-0.80	1.03	65321
EVOL	1.82	6.67	0.04	63.37	65321
ERepLag	35.94	13.37	-7.00	442.00	65321
#Estimates	8.41	6.71	1.00	45.00	65321
TURN	21.24	19.03	1.36	132.82	65321
Loss	0.29	0.45	0.00	1.00	65321
#Announcements	144.50	90.57	1.00	408.00	65321
IO	0.55	0.38	0.00	1.00	65321

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
1 SUE	1.000																				
2 BHAR[0,1]	0.340***	1.000																			
3 BHAR[2,5]	0.034***	0.015***	1.000																		
4 BHAR[2,22]	0.233***	0.630***	0.371***	1.000																	
5 BHAR[2,45]	0.035***	0.027***	0.345***	0.539***	1.000																
6 BHAR[2,next]	0.048***	0.028***	0.303***	0.480***	0.829***	1.000															
7 Log(Retail)	0.110***	0.029***	0.019***	0.022***	-0.016***	0.002	1.000														
8 Log(Nonretail)	0.119***	0.045***	0.021***	0.033***	-0.012***	0.006	0.941***	1.000													
9 #Complaints	0.015***	-0.001	0.001	0.007*	0.002	0.001	0.029***	0.021***	1.000												
10 Log(MktVol)	0.121***	0.043***	0.021***	0.035***	-0.008*	0.008*	0.951***	0.999***	0.027***	1.000											
11 PreRet	0.184***	0.261***	-0.003	0.165***	0.011**	0.025***	0.057***	0.048***	0.005	0.052***	1.000										
12 Log(Size)	0.115***	0.037***	0.013***	0.023***	-0.009**	0.005	0.810***	0.901***	0.024***	0.896***	0.050***	1.000									
13 Book-to-Market	-0.047***	0.013***	0.007*	0.030***	0.032***	0.036***	-0.188***	-0.227***	0.009*	-0.232***	0.033***	-0.264***	1.000								
14 EPersistence	0.006	-0.010**	-0.000	-0.002	0.006	0.005	0.018***	0.006	-0.010**	0.009**	0.006	-0.028***	-0.008*	1.000							
15 EVOL	-0.024***	-0.032***	-0.024***	-0.052***	-0.049***	-0.059***	-0.035***	-0.069***	-0.007*	-0.063***	-0.024***	-0.103***	0.094***	-0.041***	1.000						
16 ERepLag	-0.090***	-0.025***	-0.012***	-0.028***	-0.026***	-0.020***	-0.267***	-0.322***	0.039***	-0.320***	0.003	-0.347***	0.099***	-0.019***	0.060***	1.000					
17 #Estimates	0.073***	0.011**	0.013***	0.007	-0.003	-0.001	0.689***	0.711***	-0.016***	0.713***	0.004	0.693***	-0.116***	0.059***	-0.022***	-0.250***	1.000				
18 TURN	0.017***	-0.036***	-0.008*	-0.032***	-0.033***	-0.031***	0.369***	0.281***	0.041***	0.312***	-0.007	0.062***	0.024***	0.070***	0.172***	-0.010**	0.232***	1.000			
19 Loss	-0.215***	-0.131***	-0.023***	-0.088***	-0.019***	-0.041***	-0.219***	-0.289***	0.026***	-0.277***	-0.076***	-0.352***	0.114***	0.009*	0.135***	0.203***	-0.166***	0.164***	1.000		
20 #Announcements	0.024***	0.006	-0.011**	0.020***	0.033***	0.020***	-0.005	0.058***	-0.026***	0.066***	-0.025***	0.100***	-0.020***	0.008*	-0.016***	-0.288***	-0.008*	-0.009*	-0.009*	1.000	
21 IO	0.044***	0.023***	0.016***	0.032***	0.005	-0.007	0.301***	0.355***	0.061***	0.367***	-0.002	0.345***	-0.126***	-0.075***	-0.068***	-0.124***	0.150***	0.034***	-0.047***	0.078***	1.000

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 Announcement Returns and Retail Trading Volume

	Dependent Variable: BHAR[0,1]	
	(1)	(2)
SUE	0.366***	0.313***
	(0.0109)	(0.00638)
Log(Retail)	-0.109***	-0.251***
	(0.0343)	(0.0327)
SUE × Log(Retail)	0.266***	0.247***
	(0.0220)	(0.0186)
Log(Nonretail)	0.124***	0.468***
	(0.0397)	(0.0471)
SUE × Log(Nonretail)	-0.142***	0.317***
	(0.0194)	(0.0270)
PreRet		0.239***
		(0.0127)
Controls	No	Yes
Controls*SUE	No	Yes
Year-Quarter FE	Yes	Yes
Day-of-Week FE	Yes	Yes
Firm FE	Yes	Yes
Observations	65194	65194
Adj.R2	0.152	0.247

This table presents estimates of $BHAR[0,1]_{it} = \beta_0 + \beta_1 SUE_{it} + \beta_2 Log(Retail)_{it} + \beta_3 SUE_{it} * Log(Retail)_{it} + \sum \beta_I X_{I,it} + \sum \beta_k SUE_{it} * X_{k,it} + \epsilon_{it}$. The dependent variable, BHAR[0,1], is earnings announcement abnormal returns. The independent variable of interest is the interaction between the earnings surprise quantile (SUE) and Log(Retail) 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 in parentheses below coefficients are clustered by firm and quarter. ***, **, and * indicate statistical significance at two-sided 1%, 5%, and 10% levels, respectively.

Table 5: 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 EA]*
	(1)	(2)	(3)	(4)	(5)
SUE	0.313***	0.0278***	0.206***	0.0195***	0.0247***
	(0.00638)	(0.00633)	(0.00583)	(0.00570)	(0.00588)
Log(Retail)	-0.251***	0.0100	-0.133***	0.00874	0.0263
	(0.0327)	(0.0244)	(0.0270)	(0.0223)	(0.0237)
SUE × Log(Retail)	0.247***	0.0286	0.202***	0.0510***	0.0372***
	(0.0186)	(0.0182)	(0.0186)	(0.0130)	(0.0135)
Log(Nonretail)	0.468***	0.0992**	0.340***	0.0343	0.0260
	(0.0471)	(0.0391)	(0.0399)	(0.0409)	(0.0433)
SUE × Log(Nonretail)	0.317***	-0.0122	0.138***	-0.0716***	-0.0411*
	(0.0270)	(0.0237)	(0.0233)	(0.0212)	(0.0237)
PreRet	0.239***	-0.00556	0.141***	0.00892	0.00139
	(0.0127)	(0.0105)	(0.00947)	(0.0114)	(0.0127)
Controls	Yes	Yes	Yes	Yes	Yes
Controls*SUE	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes
Day-of-Week FE	Yes	Yes	Yes	Yes	Yes
Observations	65194	65194	65194	65194	65194
Adj.R2	0.244	0.0236	0.134	0.0531	0.0613

This table presents estimates of $BHAR[a,b]_{it} = \beta_0 + \beta_1 SUE_{it} + \beta_2 Log(Retail)_{it} + \beta_3 SUE_{it} * Log(Retail)_{it} + \beta_4 Log(Nonretail)_{it} + \beta_5 SUE_{it} * Log(Nonretail)_{it} + \sum \beta_I X_{I,it} + \sum \beta_k SUE_{it} * X_{k,it} + \epsilon_{it}$. The dependent variables, BHAR[a,b], are abnormal returns from day a to day b around the earnings announcement day 0. The independent variable of interest is the interaction between the earnings surprise quantile (SUE) and Log(Retail) during the earnings announcement window. 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, and IO. Detailed definitions of all variables are included in Appendix B. Standard errors in parentheses below coefficients are clustered by firm and quarter. ***, **, and * indicate statistical significance at two-sided 1%, 5%, and 10% levels, respectively.

Table 6: Post-earnings Announcement Drift (Non-overlapping windows)

	BHAR[6,22]	*BHAR[23,45]*	*BHAR[46,next EA]*
	(1)	(2)	(3)
SUE	0.211***	-0.185***	0.0215***
	(0.00572)	(0.00650)	(0.00639)
Log(Retail)	-0.152***	0.226***	0.0660***
	(0.0281)	(0.0283)	(0.0214)
SUE × Log(Retail)	0.202***	-0.158***	0.0227
	(0.0174)	(0.0149)	(0.0151)
Log(Nonretail)	0.336***	-0.197***	0.00732
	(0.0406)	(0.0402)	(0.0379)
SUE × Log(Nonretail)	0.162***	-0.229***	-0.00456
	(0.0211)	(0.0220)	(0.0236)
PreRet	0.151***	-0.131***	-0.00229
	(0.00948)	(0.0115)	(0.0118)
Controls	Yes	Yes	Yes
Controls*SUE	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes
Day-of-Week FE	Yes	Yes	Yes
Observations	65194	65194	65194
Adj.R2	0.137	0.107	0.00674

This table presents estimates of $BHAR[a,b]_{it} = \beta_0 + \beta_1 SUE_{it} + \beta_2 Log(Retail)_{it} + \beta_3 SUE_{it} * Log(Retail)_{it} + \beta_4 Log(Nonretail)_{it} + \beta_5 SUE_{it} * Log(Nonretail)_{it} + \sum \beta_I X_{I,it} + \sum \beta_k SUE_{it} * X_{k,it} + \epsilon_{it}$. The dependent variables, BHAR[a,b], are abnormal returns from day a to day b around the earnings announcement day 0. The independent variable of interest is the interaction between the earnings surprise quantile (SUE) and Log(Retail) during the earnings announcement window. 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, and IO. Detailed definitions of all variables are included in Appendix B. Standard errors in parentheses below coefficients are clustered by firm and quarter. ***, **, and * indicate statistical significance at two-sided 1%, 5%, and 10% levels, respectively.

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 EA]*
	(1)	(2)	(3)	(4)	(5)
SUE	0.311***	0.0425**	0.214***	0.0473***	0.0358*
	(0.0142)	(0.0175)	(0.0175)	(0.0145)	(0.0169)
Outage	-0.00434	-0.00562	0.0138	0.0579	0.0524
	(0.0247)	(0.0506)	(0.0588)	(0.0462)	(0.0466)
Outage × SUE	-0.0604**	-0.0157	0.00417	0.0318	0.0437
	(0.0250)	(0.0273)	(0.0330)	(0.0426)	(0.0483)
Log(MktVol)	0.298***	0.0718	0.276***	0.0469	0.0677
	(0.0639)	(0.0642)	(0.0640)	(0.0715)	(0.0792)
Controls	Yes	Yes	Yes	Yes	Yes
Controls*SUE	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes
Day-of-Week FE	Yes	Yes	Yes	Yes	Yes
Observations	21549	21549	21549	21549	21549
Adj.R2	0.212	0.0356	0.175	0.135	0.167

This table presents estimates of $BHAR[a,b]_{it} = \beta_0 + \beta_1 Outage_t + \beta_2 SUE_{it} + \beta_3 SUE_{it} * Outage_t + \beta_4 Log(MktVol)_{it} + \sum \beta_I X_{I,it} + \sum \beta_k SUE_{it} * X_{it} + \epsilon_{it}$ The dependent variables, BHAR[a,b], are abnormal returns from day a to day b around the earnings announcement day 0. The independent variable of interest is the interaction between the earnings surprise quantile (SUE) and Outage, an indicator for a top-quintile brokerage outage on the same day as the 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, and IO. Detailed definitions of all variables are included in Appendix B. Standard errors in parentheses below coefficients are clustered by firm and quarter. ***, **, and * indicate statistical significance at two-sided 1%, 5%, and 10% levels, respectively.

Table 9.A: Regression to orthogonalize *Log(Retail)* against recent returns

	Log(Retail)
$\text{Return}_{t-2\ to\ t-1}$	1.278^{***}
	(0.0167)
$\text{Return}_{t-5\ to\ t-2}$	1.069^{***}
	(0.0106)
Firm FE	No
Date FE	No
Observations	7426261
Adj.R2	0.00327

This table presents estimates of $Log(Retail)_{it} = \beta_0 + \beta_1 Return_{t-2\ to\ t-1} + \beta_2 Return_{t-5\ to\ t-2} + \epsilon_{it}$, estimated at the stock-day level. All variables are standardized to be mean-zero and unit-variance. Detailed definitions of all variables are included in Appendix B. Standard errors in parentheses below coefficients are clustered by firm and quarter. ***, **, and * indicate statistical significance at two-sided 1%, 5%, and 10% levels, respectively.

Table 9.B: Predicting return-orthogonalized retail trading

	Residual *Log(Retail)*
Return Skewness	-0.00192^{***}
	(0.000366)
Return Range	0.0608^{***}
	(0.00107)
Price_{t-1}	0.0902^{***}
	(0.00375)
Market Cap_{t-1}	0.0159^{***}
	(0.00598)
Log(Retail)_{t-1}	0.389^{***}
	(0.00302)
Log(MktVol)_{t-1}	0.403^{***}
	(0.00304)
Firm FE	Yes
Date FE	No
Observations	7320202
Adj.R2	0.874

This table presents estimates of $\text{Residual Log(Retail)}_{i,t} = \beta_0 + \lambda' \text{X}^{firm}_{i,t-1} + \gamma \text{Log(Retail)}_{i,t-1} + \delta \text{Log(Mkt)}_{i,t-1} + \epsilon_{i,t}$, estimated at the stock-day level. The dependent variable is the regression errors from Table 9.A. Detailed definitions of independent variables are included in Appendix B. All variables are standardized to be mean-zero and unit-variance. Standard errors in parentheses below coefficients are clustered by firm and quarter. ***, **, and * indicate statistical significance at two-sided 1%, 5%, and 10% levels, respectively.

Table 9.C: Earnings Announcement Returns, Post-earnings Announcement Drift, and Retail Frictions with Predicted Retail Trade

	BHAR[0,1]	*BHAR[2,5]*	*BHAR[2,22]*	*BHAR[2,45]*	*BHAR[2,next EA]*
	(1)	(2)	(3)	(4)	(5)
SUE	0.209**	0.195**	0.0951	0.0951	-0.0262
	(0.0854)	(0.0946)	(0.0947)	(0.0947)	(0.0888)
Outage	0.0133	0.0230	0.0726***	0.0726***	0.0490**
	(0.0207)	(0.0230)	(0.0230)	(0.0230)	(0.0216)
$ERetail^{TQ}$	-0.296***	-0.00423	-0.168***	-0.168***	0.113***
	(0.0229)	(0.0254)	(0.0254)	(0.0254)	(0.0238)
Outage × SUE × $ERetail^{TQ}$	-0.0592**	0.0509	-0.0280	-0.0280	0.0493*
	(0.0281)	(0.0312)	(0.0312)	(0.0312)	(0.0293)
Outage × SUE	-0.0166	-0.0146	0.0162	0.0162	0.0130
	(0.0188)	(0.0208)	(0.0208)	(0.0208)	(0.0195)
SUE × $ERetail^{TQ}$	0.0484**	0.0145	0.0181	0.0181	-0.00623
	(0.0196)	(0.0217)	(0.0218)	(0.0218)	(0.0204)
Outage × $ERetail^{TQ}$	-0.0432	0.0616*	0.0453	0.0453	0.00219
	(0.0289)	(0.0320)	(0.0320)	(0.0320)	(0.0300)
Controls	Yes	Yes	Yes	Yes	Yes
Controls*SUE	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes
Day-of-Week FE	Yes	Yes	Yes	Yes	Yes
Observations	20649	20649	20629	20629	20649
Adj.R2	0.152	0.00464	0.0743	0.0743	0.0184

This table presents estimates of $BHAR[a,b]_{it} = \beta_0 + \beta_1 Outage_t + \beta_2 SUE_{it} + \beta_3 ERetail^{TQ} + \beta_4 SUE_{it} * Outage_t + \beta_5 SUE_{it} * ERetail^{TQ} + \beta_6 Outage_t * ERetail^{TQ} + \beta_7 SUE_{it} * Outage_t * ERetail^{TQ} + \sum \beta_I X_{I,it} + \sum \beta_k SUE_{it} * X_{it} + \epsilon_{it}$. The dependent variables, BHAR[a,b], are abnormal returns from day a to day b around the earnings announcement day 0. The independent variable of interest is the triple interaction between the earnings surprise quantile (SUE), Outage, an indicator for a top-quintile brokerage outage on the same day as the earnings announcement, and $Retail^{TQ}$, an indicator for predicted top-quintile retail trade. 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 in parentheses below coefficients are clustered by firm and quarter. ***, **, and * indicate statistical significance at two-sided 1%, 5%, and 10% levels, respectively.

Table 10: Retail Order Imbalance

	Dependent Variable: BHAR[0,1]	
	(1)	(2)
SUE	0.373***	0.341***
	(0.00951)	(0.00702)
Retail OIB	-0.00913	-0.00293
	(0.00928)	(0.00838)
SUE × Retail OIB	0.00407	0.000757
	(0.00517)	(0.00493)
Controls	No	Yes
Controls*SUE	No	Yes
Year-Quarter FE	Yes	Yes
Day-of-Week FE	Yes	Yes
Firm FE	Yes	Yes
Observations	65194	65194
Adj.R2	0.137	0.205

This table presents estimates of $BHAR[0,1]_{it} = \beta_0 + \beta_1 SUE_{it} + \beta_2 RetailOIB_{it} + \beta_3 SUE_{it} * RetailOIB_{it} + \sum \beta_I X_{I,it} + \sum \beta_k SUE_{it} * X_{k,it} + \epsilon_{it}$. The dependent variable, BHAR[0,1], is abnormal returns during the earnings announcement window. The independent variables of interest are Retail OIB (order imbalance) and its interaction with the earnings surprise quantile (SUE). 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, and IO. Detailed definitions of all variables are included in Appendix B. Standard errors in parentheses below coefficients are clustered by firm and quarter. ***, **, and * indicate statistical significance at two-sided 1%, 5%, and 10% levels, respectively.

Table 11: Liquidity and Retail Frictions with Predicted Retail Trade

	Quoted Spread	*Effective Spread*	*Depth*
	(1)	(2)	(3)
Outage	-0.0469	-0.0671	72.11
	(0.0393)	(0.0492)	(103.4)
$ERetail^{TQ}$	-0.0024	0.0419	166.6**
	(0.0576)	(0.0722)	(43.67)
Outage × $ERetail^{TQ}$	0.1082*	0.1552*	-207.0***
	(0.0649)	(0.0861)	(41.98)
SUE	0.02026***	0.0263***	-244.8***
	(0.0035)	(0.0044)	(29.03)
Year-Quarter FE	Yes	Yes	Yes
Day-of-Week FE	Yes	Yes	Yes
Observations	20649	20649	20629
Adj.R2	0.0212	0.0189	0.0128

This table presents estimates of $Liq_{it} = \beta_0 + \beta_1 Outage_t + \beta_2 ERetail^{TQ} + \beta_3 Outage_t * ERetail^{TQ} + \beta_4 SUE_{it} + \epsilon_{it}$. The dependent variables, Liq, are earnings announcement day Quoted Spread, Effective Spread, and Depth. The independent variable of interest is the interaction between an indicator for a top-quintile brokerage outage on the same day as the earnings announcement, and Retail^{TQ} and an indicator for predicted top-quintile retail trade. All variables are standardized to be mean-zero and unit-variance. Control variables include the earnings surprise quantile (SUE). Detailed definitions of all variables are included in Appendix B. Standard errors in parentheses below coefficients are clustered by firm and quarter. ***, **, and * indicate statistical significance at two-sided 1%, 5%, and 10% levels, respectively.

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A Additional analysis

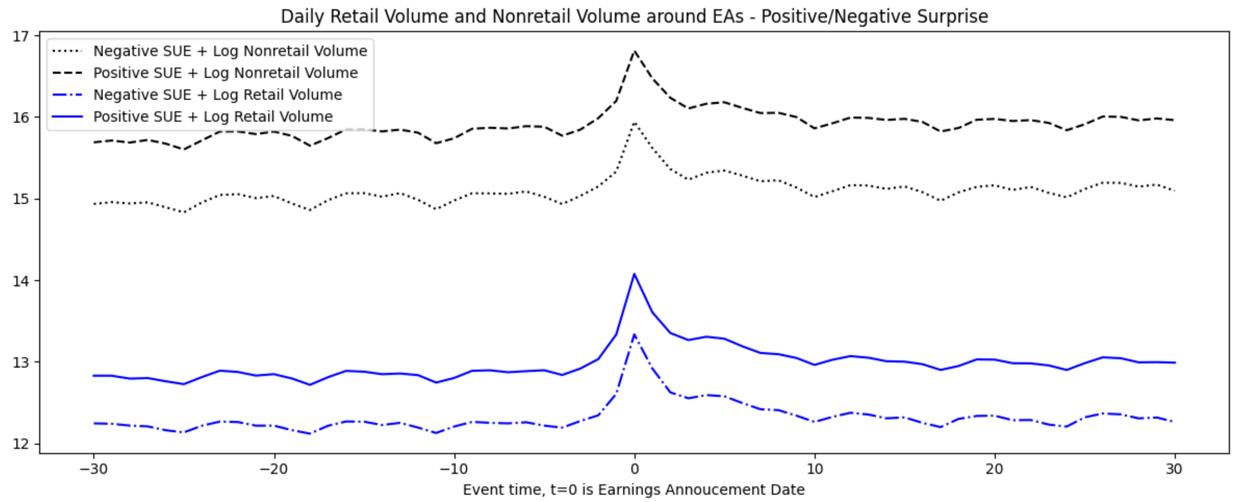

Figure A.1: Daily Retail and Nonretail Volume around earnings announcements for positive and negative earnings surprises.

Table A.1: Retail Trading Volume and Brokerage Outages

	Dep var: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 estimates of $Log(Retail)_{it} = \beta_0 + \beta_1 Outage_t + \beta_2 Log(NonRetail)_{it} + \gamma_i + \delta_t + \epsilon_{it}$. 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 in parentheses below coefficients are clustered by firm and time of the day. ***, **, and * indicate statistical significance at two-sided 1%, 5%, and 10% levels, respectively.

Table A.2: Descriptive Statistics for Earnings Announcements with and without Outages

	Outage=0			*Outage=1*			
	N	mean	sd	N	mean	sd	Diff
SUE(raw)	21228	-0.00	0.10	321	0.00	0.04	-0.001
SUE	21228	7.07	3.23	321	7.29	3.23	0.145
BHAR[0,1]	21228	-0.00	0.09	321	-0.00	0.09	0.007
BHAR[2,5]	21228	-0.00	0.06	321	-0.01	0.06	-0.016**
BHAR[2,22]	21228	-0.00	0.16	321	0.00	0.18	0.007
BHAR[2,45]	21228	-0.01	0.18	321	0.01	0.21	0.023
BHAR[2,next]	21228	-0.01	0.20	321	0.02	0.23	0.022
#Complaints	21228	525.80	2097.16	321	12598.00	0.00	11,704.577***
Log(Retail)	21228	14.60	2.03	321	14.64	1.95	-0.071
Log(Nonretail)	21228	17.18	2.20	321	17.25	2.16	-0.063
PreRetail	21228	15.35	1.89	321	15.60	1.99	-0.024
PreNonretail	21228	18.10	2.13	321	18.24	2.18	-0.097
Log(MktVol)	21228	17.28	2.16	321	17.35	2.12	-0.060
PreRet	21228	0.01	0.11	321	0.00	0.17	-0.004
Log(Size)	21228	7.19	1.89	321	7.26	2.00	-0.054
Book-to-Market	21228	0.68	0.88	321	0.66	0.56	-0.016
EPersistence	21228	0.12	0.34	321	0.15	0.35	-0.002
EVOL	21228	1.80	6.01	321	1.41	3.19	-0.063
ERepLag	21228	37.58	13.55	321	42.11	25.04	-2.640
#Estimates	21228	7.65	6.10	321	7.58	6.04	0.137
TURN	21228	23.67	23.51	321	23.03	21.90	-1.246**
Loss	21228	0.36	0.48	321	0.37	0.48	0.022
#Announcements	21228	143.67	92.98	321	84.47	53.31	-1.737
IO	21228	0.71	0.25	321	0.65	0.23	-0.007

This table presents comparative descriptive statistics for the sample, distinguishing between earnings announcements that experienced outage incidents ($Outage = 1$) and those that did not ($Outage = 0$) within a 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.

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 EA]*
	(1)	(2)	(3)	(4)	(5)
SUE	0.313***	0.0247***	0.244***	0.00408	0.0118**
	(0.00638)	(0.00631)	(0.00677)	(0.00888)	(0.00562)
Log(Retail)	-0.251***				
	(0.0327)				
SUE × Log(Retail)	0.247***				
	(0.0186)				
Log(Nonretail)	0.468***				
	(0.0471)				
SUE × Log(Nonretail)	0.317***				
	(0.0270)				
Log(Retail)[2,5]		0.142***			
		(0.0236)			
SUE × Log(Retail)[2,5]		0.0628***			
		(0.0178)			
Log(Nonretail)[2,5]		0.499***			
		(0.0474)			
SUE × Log(Nonretail)[2,5]		-0.0116			
		(0.0223)			
Log(Retail)[2,22]			-0.0752*		
			(0.0414)		
SUE × Log(Retail)[2,22]			0.114***		
			(0.0223)		
Log(Nonretail)[2,22]			1.119***		
			(0.0666)		
SUE × Log(Nonretail)[2,22]			0.0975***		
			(0.0251)		
Log(Retail)[2,45]				-0.0223	
				(0.0559)	
SUE × Log(Retail)[2,45]				0.0562***	
				(0.0167)	
Log(Nonretail)[2,45]				1.312***	
				(0.108)	
SUE × Log(Nonretail)[2,45]				-0.0669**	
				(0.0273)	
Log(Retail)[2,next]					-0.0435
					(0.0633)
SUE × Log(Retail)[2,next]					0.0670***
					(0.0195)
Log(Nonretail)[2,next]					1.440***
					(0.128)
SUE × Log(Nonretail)[2,next]					-0.0651*
					(0.0329)
Controls	Yes	Yes	Yes	Yes	Yes
Controls*SUE	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	65194	64882	63657	62536	65192
Adj.R2	0.247	0.0592	0.200	0.178	0.183

This table presents estimates of $BHAR[a,b]_{it} = \beta_0 + \beta_1 SUE_{it} + \beta_2 Log(Retail)[a,b]_{it} + \beta_3 SUE_{it} * Log(Retail)[a,b]_{it} + \beta_4 Log(Nonretail)[a,b]_{it} + \beta_5 SUE_{it} * Log(Nonretail)[a,b]_{it} + \sum \beta_I X_{I,it} + \sum \beta_k SUE_{it} * X_{k,it} + \epsilon_{it}$, 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, and IO. Controls are suppressed. Detailed definitions of all variables are included in Appendix B. Standard errors in parentheses below coefficients are clustered by firm and quarter. ***, **, and * indicate statistical significance at two-sided 1%, 5%, and 10% levels, respectively.

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 EA]*
	(1)	(2)	(3)	(4)	(5)
SUE	0.296***	0.0280***	0.197***	0.0184**	0.0228***
	(0.00856)	(0.00871)	(0.00822)	(0.00694)	(0.00797)
Log(Retail)	-0.147***	-0.00102	-0.0890**	-0.0347	-0.0143
	(0.0326)	(0.0423)	(0.0409)	(0.0413)	(0.0378)
SUE × Log(Retail)	0.239***	0.0177	0.192***	0.0399**	0.0223
	(0.0210)	(0.0226)	(0.0214)	(0.0171)	(0.0192)
Log(Nonretail)	0.539***	0.153**	0.432***	0.0975	0.0899
	(0.0507)	(0.0641)	(0.0562)	(0.0620)	(0.0640)
SUE × Log(Nonretail)	0.294***	0.00930	0.131***	-0.0619**	-0.0301
	(0.0300)	(0.0268)	(0.0254)	(0.0249)	(0.0300)
PreRet	0.200***	-0.00702	0.121***	0.0161	0.0132
	(0.0126)	(0.0128)	(0.0104)	(0.0117)	(0.0127)
Controls	Yes	Yes	Yes	Yes	Yes
Controls*SUE	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes
Day-of-Week FE	Yes	Yes	Yes	Yes	Yes
Observations	26317	26317	26317	26317	26317
Adj.R2	0.290	0.0308	0.184	0.0998	0.119

This table presents estimates of $BHAR[a,b]_{it} = \beta_0 + \beta_1 SUE_{it} + \beta_2 Log(Retail)_{it} + \beta_3 SUE_{it} * Log(Retail)_{it} + \beta_4 Log(Nonretail)_{it} + \beta_5 SUE_{it} * Log(Nonretail)_{it} + \sum \beta_I X_{I,it} + \sum \beta_k SUE_{it} * X_{k,it} + \epsilon_{it}$ on a sample limited to earnings announcements in extreme SUE quantiles (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 in parentheses below coefficients are clustered by firm and quarter. ***, **, and * indicate statistical significance at two-sided 1%, 5%, and 10% levels, respectively.

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 EA]*
	(1)	(2)	(3)	(4)	(5)
SUE	0.242***	0.0300**	0.153***	0.00725	0.00513
	(0.0100)	(0.0121)	(0.0117)	(0.0104)	(0.0103)
Log(Retail)	-0.262***	0.0337	-0.117**	-0.0263	-0.0159
	(0.0520)	(0.0533)	(0.0571)	(0.0567)	(0.0510)
SUE × Log(Retail)	0.283***	0.00360	0.262***	0.0811***	0.0758**
	(0.0317)	(0.0332)	(0.0305)	(0.0250)	(0.0283)
Log(Nonretail)	0.516***	0.0132	0.308***	0.0355	0.0209
	(0.0765)	(0.0869)	(0.0724)	(0.0861)	(0.0809)
SUE × Log(Nonretail)	0.265***	0.0224	0.0993***	-0.0832**	-0.0344
	(0.0398)	(0.0383)	(0.0349)	(0.0327)	(0.0356)
PreRet	0.211***	-0.00292	0.122***	-0.00638	-0.00695
	(0.0182)	(0.0186)	(0.0176)	(0.0161)	(0.0156)
Controls	Yes	Yes	Yes	Yes	Yes
Controls*SUE	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes
Day-of-Week FE	Yes	Yes	Yes	Yes	Yes
Observations	18555	18555	18555	18555	18555
Adj.R2	0.215	0.0303	0.142	0.0948	0.109

This table presents estimates of $BHAR[a,b]_{it} = \beta_0 + \beta_1 SUE_{it} + \beta_2 Log(Retail)_{it} + \beta_3 SUE_{it} * Log(Retail)_{it} + \sum \beta_I X_{I,it} + \sum \beta_k SUE_{it} * X_{k,it} + \epsilon_{it}$ in a subsample of 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 in parentheses below coefficients are clustered by firm and quarter. ***, **, and * indicate statistical significance at two-sided 1%, 5%, and 10% levels, respectively.

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

	BHAR[0,1]		*BHAR[2,5]*		*BHAR[2,22]*		*BHAR[2,45]*		*BHAR[2,next EA]*	
	Positive	Negative	Positive	Negative	Positive	Negative	Positive	Negative	Positive	Negative
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
SUE	0.502***	0.348***	0.0627**	0.00804	0.333***	0.231***	0.0343	0.0169	0.0374	0.00491
	(0.0228)	(0.0278)	(0.0261)	(0.0257)	(0.0228)	(0.0281)	(0.0263)	(0.0286)	(0.0244)	(0.0294)
Log(Retail)	-0.344***	-0.448***	-0.0930**	0.0730	-0.237***	-0.225**	-0.0240	0.105	0.0127	0.0857
	(0.0553)	(0.0822)	(0.0397)	(0.0924)	(0.0455)	(0.0865)	(0.0465)	(0.0914)	(0.0426)	(0.0881)
SUE × Log(Retail)	0.481***	0.185***	0.0884	0.0582	0.367***	0.154**	0.0440	0.0857	0.0214	0.0457
	(0.0502)	(0.0622)	(0.0596)	(0.0721)	(0.0573)	(0.0720)	(0.0627)	(0.0740)	(0.0556)	(0.0680)
Log(Nonretail)	0.239***	-0.185	0.125**	0.0615	0.236***	-0.214*	0.103	-0.0935	0.0962	-0.0199
	(0.0717)	(0.113)	(0.0598)	(0.118)	(0.0667)	(0.115)	(0.0680)	(0.136)	(0.0605)	(0.141)
SUE × Log(Nonretail)	0.527***	-0.211**	0.0273	-0.0116	0.283***	-0.245**	-0.0779	-0.104	-0.0572	-0.0144
	(0.0739)	(0.0829)	(0.0851)	(0.0883)	(0.0782)	(0.0923)	(0.0788)	(0.101)	(0.0725)	(0.106)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls*SUE	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
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	39220	20835	39220	20835	39220	20835	39220	20835	39220	20835
Adj.R2	0.209	0.205	0.0467	0.0535	0.162	0.138	0.111	0.105	0.120	0.117
	Difference in SUE × Log(Retail) coefficients									
	0.296**		0.0302		0.2130*		-0.0417		-0.0243	
	0.0808		(0.1014)		(0.0929)		(0.1061)		(0.0929)	

This table presents estimates of $BHAR[a,b]_{it} = \beta_0 + \beta_1 SUE_{it} + \beta_2 Log(Retail)[a,b]_{it} + \beta_3 SUE_{it} * Log(Retail)[a,b]_{it} + \beta_4 Log(Nonretail)[a,b]_{it} + \beta_5 SUE_{it} * Log(Nonretail)[a,b]_{it} + \sum \beta_I X_{I,it} + \sum \beta_k SUE_{it} * X_{k,it} + \epsilon_{it}$. 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 in parentheses below coefficients 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.

Table A.7: 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 EA]*	
	Small	Big	Small	Big	Small	Big	Small	Big	Small	Big
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
SUE	0.371***	0.334***	-0.000645	-0.00605	0.210***	0.197***	-0.0293*	0.00104	-0.0195	-0.00200
	(0.0149)	(0.0158)	(0.0166)	(0.0133)	(0.0159)	(0.0130)	(0.0168)	(0.0139)	(0.0175)	(0.0136)
Log(Retail)	-0.159***	-0.357***	-0.0198	0.0114	-0.0888***	-0.202***	-0.0176	0.00645	0.00792	0.0218
	(0.0348)	(0.0409)	(0.0385)	(0.0242)	(0.0309)	(0.0377)	(0.0307)	(0.0303)	(0.0344)	(0.0306)
SUE × Log(Retail)	0.222***	0.372***	-0.00235	-0.000631	0.180***	0.246***	0.0356*	0.0136	0.0201	-0.00543
	(0.0202)	(0.0309)	(0.0246)	(0.0249)	(0.0228)	(0.0245)	(0.0202)	(0.0182)	(0.0238)	(0.0202)
Log(Nonretail)	0.466***	0.427***	0.162***	0.0573	0.392***	0.257***	0.113**	-0.0153	0.0934*	-0.0243
	(0.0512)	(0.0599)	(0.0532)	(0.0398)	(0.0425)	(0.0513)	(0.0478)	(0.0415)	(0.0527)	(0.0419)
SUE × Log(Nonretail)	0.289***	0.283***	0.0472	0.0101	0.144***	0.148***	-0.0221	-0.0658**	0.00547	-0.0276
	(0.0299)	(0.0479)	(0.0326)	(0.0345)	(0.0274)	(0.0392)	(0.0256)	(0.0284)	(0.0319)	(0.0288)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls*SUE	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	26714	38336	26714	38336	26714	38336	26714	38336	26714	38336
Adj.R2	0.245	0.270	0.0403	0.0386	0.172	0.178	0.111	0.106	0.126	0.112
	Difference in SUE × Log(Retail) coefficients									
	-0.1500***		0.0017		-0.0660**		0.0220		0.0255	
	(0.0311)		(0.029)		0.0321)		(0.0305)		(0.0316)	

This table presents estimates of $BHAR[a,b]_{it} = \beta_0 + \beta_1 SUE_{it} + \beta_2 Log(Retail)[a,b]_{it} + \beta_3 SUE_{it} * Log(Retail)[a,b]_{it} + \beta_4 Log(Nonretail)[a,b]_{it} + \beta_5 SUE_{it} * Log(Nonretail)[a,b]_{it} + \sum \beta_I X_{I,it} + \sum \beta_k SUE_{it} * X_{k,it} + \epsilon_{it}$. 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 in parentheses below coefficients 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.

Table A.8: 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 EA]*	
	Normal	Busy	Normal	Busy	Normal	Busy	Normal	Busy	Normal	Busy
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
SUE	0.305	0.680***	0.529	0.0298	0.570	0.419***	0.617	-0.0269	0.963**	-0.0159
	(0.386)	(0.0935)	(0.375)	(0.118)	(0.350)	(0.0802)	(0.374)	(0.112)	(0.415)	(0.117)
Log(Retail)	-0.230***	-0.101	-0.00359	-0.0553	-0.0985	-0.0741	0.139*	0.0335	0.181**	0.0436
	(0.0735)	(0.0605)	(0.0620)	(0.0596)	(0.0781)	(0.0629)	(0.0758)	(0.0579)	(0.0784)	(0.0643)
SUE × Log(Retail)	0.445***	0.302***	0.00238	0.0496	0.324***	0.206***	0.0992	-0.0112	0.0791	-0.0207
	(0.0737)	(0.0541)	(0.0729)	(0.0567)	(0.0656)	(0.0469)	(0.0629)	(0.0442)	(0.0600)	(0.0555)
Log(Nonretail)	0.550***	0.154	0.167	0.253**	0.422***	0.181*	-0.106	0.0566	-0.102	-0.0251
	(0.128)	(0.0961)	(0.113)	(0.0970)	(0.115)	(0.0936)	(0.128)	(0.0992)	(0.122)	(0.0937)
SUE × Log(Nonretail)	-0.180**	-0.125**	-0.0400	-0.112	-0.177**	-0.0934*	-0.104	-0.00727	-0.0979	0.0287
	(0.0708)	(0.0529)	(0.0799)	(0.0734)	(0.0666)	(0.0525)	(0.0697)	(0.0566)	(0.0611)	(0.0641)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls*SUE	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	31027	33812	31027	33812	31027	33812	31027	33812	31027	33812
Adj.R2	0.216	0.251	0.0363	0.0538	0.157	0.166	0.107	0.111	0.109	0.122
	Difference in SUE × Log(Retail) coefficients									
	0.1430		-0.04722		0.1180		0.1068		-0.0903	
	(0.0922)		(0.0951)		(0.0785)		(0.0806)		(0.0956)	

This table presents estimates of $BHAR[a,b]_{it} = \beta_0 + \beta_1 SUE_{it} + \beta_2 Log(Retail)[a,b]_{it} + \beta_3 SUE_{it} * Log(Retail)[a,b]_{it} + \beta_4 Log(Nonretail)[a,b]_{it} + \beta_5 SUE_{it} * Log(Nonretail)[a,b]_{it} + \sum \beta_I X_{I,it} + \sum \beta_k SUE_{it} * X_{k,it} + \epsilon_{it}$. The sample split is based on busy versus non-busy EA days, where busy days are those with above-median number of concurrent 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 in parentheses below coefficients 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: $BHAR[a,b]_{it} = \beta_0 + \beta_1 SUE_{it} + \beta_2 Log(Retail)_{it} + \beta_3 SUE_{it} * Log(Retail)_{it} + \beta_4 Log(Nonretail)_{it} + \beta_5 SUE_{it} * Log(Nonretail)_{it} + \sum \beta_{k+6} X_{k,it} + \sum \beta_{k+6} SUE_{it} * X_{k,it} + \epsilon_{it}$

Table A.9: 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 EA]*	
	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	0.331***	0.314***	0.0294***	0.000333	0.219***	0.209***	0.0157**	0.0168	0.0227***	0.0298***
	(0.00860)	(0.0112)	(0.00629)	(0.0106)	(0.00804)	(0.00924)	(0.00764)	(0.0101)	(0.00746)	(0.00963)
Log(Retail)	-0.256***	-0.241***	0.00283	-0.0329	-0.122***	-0.140***	0.0328	-0.00323	0.0580**	0.00438
	(0.0413)	(0.0405)	(0.0258)	(0.0329)	(0.0338)	(0.0382)	(0.0254)	(0.0321)	(0.0265)	(0.0336)
SUE × Log(Retail)	0.365***	0.330***	0.0284	0.0418*	0.215***	0.230***	0.0317**	0.0473*	0.0321*	0.0418
	(0.0233)	(0.0341)	(0.0182)	(0.0248)	(0.0236)	(0.0336)	(0.0195)	(0.0245)	(0.0177)	(0.0285)
Log(Nonretail)	0.519***	0.415***	0.106***	0.144***	0.369***	0.302***	0.0402	0.0239	0.0217	0.0252
	(0.0625)	(0.0647)	(0.0388)	(0.0531)	(0.0557)	(0.0528)	(0.0461)	(0.0622)	(0.0465)	(0.0588)
SUE × Log(Nonretail)	-0.178***	-0.140***	-0.0479***	-0.0408	-0.181***	-0.129***	-0.0753***	-0.0842***	-0.0615***	-0.0710**
	(0.0223)	(0.0374)	(0.0167)	(0.0298)	(0.0222)	(0.0379)	(0.0215)	(0.0252)	(0.0190)	(0.0293)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls*SUE	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	39141	21657	39141	21657	39141	21657	39141	21657	39141	21657
Adj.R2	0.216	0.251	0.0363	0.0538	0.157	0.166	0.107	0.111	0.109	0.122
	Difference in SUE × Log(Retail) coefficients									
	0.0350		-0.0134		-0.0150		-0.0156		-0.0097	
	(0.0367)		(0.0257)		(0.0361)		(0.0290)		(0.0327)	

This table presents estimates of $BHAR[a,b]_{it} = \beta_0 + \beta_1 SUE_{it} + \beta_2 Log(Retail)[a,b]_{it} + \beta_3 SUE_{it} * Log(Retail)[a,b]_{it} + \beta_4 Log(Nonretail)[a,b]_{it} + \beta_5 SUE_{it} * Log(Nonretail)[a,b]_{it} + \sum \beta_I X_{I,it} + \sum \beta_k SUE_{it} * X_{k,it} + \epsilon_{it}$. The sample split is based on the weekday 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 in parentheses below coefficients 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.

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

	Dependent Variable: BHAR[0,1]			
	Original Sample	*Entropy Balanced Sample*	using Log(#Complaints) as Outage	*Randomized Outages*
SUE	0.311***	0.317***	0.310***	0.304***
	(0.0142)	(0.0272)	(0.0143)	(0.0146)
Outage	-0.00434	0.00628	-0.000540	0.00363
	(0.0247)	(0.0343)	(0.00287)	(0.0210)
Outage × SUE	-0.0604**	-0.0553**	-0.00689**	-0.000150
	(0.0250)	(0.0246)	(0.00317)	(0.0229)
Log(MktVol)	0.298***	0.498***	0.298***	0.300***
	(0.0639)	(0.102)	(0.0640)	(0.0642)
Controls*SUE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Day-of-Week FE	Yes	Yes	Yes	Yes
Observations	21549	21549	21549	21549
Adj.R2	0.212	0.385	0.212	0.212

This table presents estimates of $BHAR[0,1]_{it} = \beta_0 + \beta_1 SUE_{it} + \beta_2 Outage_t + \beta_3 SUE_{it} * Outage_t + \beta_4 Log(MktVol)_{it} + \beta_5 SUE_{it} * Log(MktVol)_{it} + \sum \beta_I X_{I,it} + \sum \beta_k SUE_{it} * X_{k,it} + \epsilon_{it}$. 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) defines *Outage* as the number of complaints rather than an indicator for top-quintile outage complaint days. Column (4) 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, and IO. Detailed definitions of all variables are included in Appendix B. Standard errors in parentheses below coefficients are clustered by firm and quarter. ***, **, and * indicate statistical significance at two-sided 1%, 5%, and 10% levels, respectively.

Table A.11: Robustness Tests: Various Definitions of Brokerage Outages

	Dependent Variable: BHAR[0,1]			
Indicator for EA days with outages:	*above-median*	*top-tercile*	*top-quartile*	*top-quintile*
SUE	0.305***	0.306***	0.305***	0.311***
	(0.0146)	(0.0147)	(0.0143)	(0.0142)
Outage	0.0189	0.0202	0.0525	-0.00434
	(0.0274)	(0.0300)	(0.0388)	(0.0247)
Outage × SUE	-0.0662*	-0.0765*	-0.0721*	-0.0604**
	(0.0393)	(0.0387)	(0.0403)	(0.0250)
Log(MktVol)	0.299***	0.299***	0.299***	0.298***
	(0.0642)	(0.0643)	(0.0642)	(0.0639)
Controls*SUE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Day-of-Week FE	Yes	Yes	Yes	Yes
Observations	21549	21549	21549	21549
# of observations where Outage = 1	1149	745	350	321
Adj.R2	0.211	0.211	0.211	0.212

This table presents estimates of $BHAR[0,1]_{it} = \beta_0 + \beta_1 SUE_{it} + \beta_2 Outage_t + \beta_3 SUE_{it} * Outage_t + \beta_4 Log(MktVol)_{it} + \beta_5 SUE_{it} * Log(MktVol)_{it} + \sum \beta_I X_{I,it} + \sum \beta_k SUE_{it} * X_{k,it} + \epsilon_{it}$ with $Outage$ defined based on different top-quantiles in each column. 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, and IO. Detailed definitions of all variables are included in Appendix B. Standard errors in parentheses below coefficients are clustered by firm and quarter. ***, **, 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 $BHAR[s,t]_{i,q} = \prod_{d=s}^{t}(1 + ret_{i,d}) - \prod_{d=s}^{t}(1 + ret_{p,d})$, 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 intra-quarter quantile as in DellaVigna and Pollet (2009). Source: IBES, CRSP.
Outage	A dummy variable set to one if the total number of 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 of one plus the dollar volume of shares traded by retail investors over the earnings announcement window. Retail trades are identified following the Boehmer et al. (2021) approach. Source: TAQ.
Log(NonRetail)	Log of one plus dollar market volume less retail trading volume over the earnings announcement window. Source: TAQ.
# Complaints	Total number of retail brokerage outage complaints in the earnings-announcement window or a 5-minute trading interval. Source: Downdetector.com (Eaton et al., 2022).
Size	Market value of equity on the earnings announcement date in $M. Source: CRSP.
PreRet	Pre-earnings announcement returns. Compound excess return over the size portfolio for earnings announcement trading date -10 to -1 relative to announcement date 0. Source: CRSP.
Book-to-Market	Book to market ratio at the end of the 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 same-day earnings announcements. Source: IBES.
Log(MktVol)	Log value of market volume during the 2-day earnings announcement window in \$M. Source: CRSP.
Retail OIB	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.
$\text{Return}_{s,t}$	Firm i's return from trading day s through day t. Source: CRSP.
Return Skewness	Skewness of a firm's daily returns over the past 60 days, calculated as the third central moment about the mean of daily returns, following Harvey and Siddique (2000). Winsorized at 1st and 99th percentiles. Source: CRSP.
Return Range	The range in stock value over the preceding 60-day period, calculated as the difference between the highest and lowest closing prices during this timeframe. Source: CRSP.
Price_{t-1}	The price of the stock on day $t-1$. Source: CRSP.
Market Cap_{t-1}	Firm i's total market value on the preceding day ($t-1$), calculated by multiplying the firm's stock price by its total number of outstanding shares. The resultant market equity is log transformed and lagged by one day. Winsorized at 1st and 99th percentiles. Source: CRSP.
Quoted Spread	Firm i's closing percent quoted spread on day t (in bps). Winsorized at 1st and 99th percentiles. Source: WRDS Millisecond Intraday Indicators.
Effective Spread	Firm i's average percent effective spread on day t (in bps). Winsorized at 1st and 99th percentiles. Source: WRDS Millisecond Intraday Indicators.
Depth	Firm i's depth, measured as bid depth plus offer depth on day t. We use the time-weighted best bid and offer share depths during market hours. Winsorized at 1st and 99th percentiles. Source: WRDS Millisecond Intraday Indicators.

C Supporting Calculations for Section 3

Overall, the conditional probabilities of trade are as follows:

1. $\frac{\gamma}{\gamma+\rho}$ = probability of informed trade on the public market conditional on the order being routed to the public market;

2. $\frac{\rho}{\gamma+\rho}$ = probability of uninformed retail trade on the public market conditional on the order being routed to the public market;

3. 1 = probability of uninformed retail trade conditional on the trade being routed to the PFOF venue.

Conditional values from the PMM's perspective are:

$$\begin{aligned}
E[v|\text{buy}] &= \Pr(\text{informed \& buy}|\text{buy}) * v_H + \Pr(\text{retail \& buy }|\text{buy}) * v_0 \\
&= \frac{\gamma}{(\gamma+\rho)} * (v_0+\sigma) + \frac{\rho}{(\gamma+\rho)} * v_0 \\
&= v_0 + \sigma\frac{\gamma}{\gamma+\rho}, \text{ and} \\
E[v|\text{sell}] &= \Pr(\text{informed \& sell}|\text{sell}) * v_L + \Pr(\text{retail \& sell }|\text{sell}) * v_0 \\
&= \frac{\gamma}{(\gamma+\rho)} * (v_0-\sigma) + \frac{\rho}{(\gamma+\rho)} * v_0 \\
&= v_0 - \sigma\frac{\gamma}{\gamma+\rho}.
\end{aligned}$$

The IMM's bid and ask prices are derived as:

$$\begin{aligned}
p_A^{IMM} &= v_0 + \sigma\frac{\gamma}{\gamma+\rho} - Z \\
&= v_0 + \sigma\frac{\gamma}{\gamma+\rho} - \frac{\omega\left(\sigma\frac{\gamma}{\gamma+\rho} - K\right)}{\gamma+\rho+\omega} \\
&= v_0 + \sigma\frac{\gamma}{\gamma+\rho} - \left(\sigma\frac{\gamma}{\gamma+\rho}\right)\frac{\omega}{\gamma+\rho+\omega} + \frac{\omega K}{\gamma+\rho+\omega} \\
&= v_0 + \sigma\frac{\gamma}{\gamma+\rho} * \frac{\gamma+\rho}{\gamma+\rho+\omega} + \frac{\omega K}{\gamma+\rho+\omega} \\
&= v_0 + \sigma\frac{\gamma}{\gamma+\rho+\omega} + \frac{\omega K}{\gamma+\rho+\omega}, \text{ and} \\
p_B^{IMM} &= v_0 - \sigma\frac{\gamma}{\gamma+\rho} + Z \\
&= v_0 - \sigma\frac{\gamma}{\gamma+\rho+\omega} - \frac{\omega K}{\gamma+\rho+\omega}.
\end{aligned}$$

The sign of the main comparative static, $\frac{d}{d\omega}S^{IMM} < 0$ can be shown, as

$$\begin{aligned}\frac{d}{d\omega}S^{IMM} &= -2\sigma\frac{\gamma}{(\gamma+\rho+\omega)^2} + 2K\frac{\gamma+\rho}{(\gamma+\rho+\omega)^2} \\ &= 2\frac{K(\gamma+\rho)-\sigma\gamma}{(\gamma+\rho+\omega)^2} < 0.\end{aligned}$$

Where $K(\gamma+\rho)-\sigma\gamma < 0$ follows from

$$\begin{aligned} Z &> 0 \\ \Leftrightarrow S^{IMM} &< S^{PMM} \\ \Leftrightarrow 2\sigma\frac{\gamma}{\gamma+\rho+\omega} + 2K\frac{\omega}{\gamma+\rho+\omega} &< 2\sigma\frac{\gamma}{\gamma+\rho} \\ \Leftrightarrow \frac{\sigma\gamma+K\omega}{\gamma+\rho+\omega} &< \frac{\sigma\gamma}{\gamma+\rho} \\ \Leftrightarrow (\sigma\gamma+K\omega)(\gamma+\rho) &< \sigma\gamma(\gamma+\rho+\omega) \\ \Leftrightarrow K(\gamma+\rho)-\sigma\gamma &< 0.\end{aligned}$$