Review of Accounting Studies
https://doi.org/10.1007/s11142-024-09825-9

Retail investor trade and the pricing of earnings

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Accepted: 15 April 2024

Abstract

Using the number of Robinhood users holding a firm's shares, I examine how novice retail investors respond to earnings announcements and the implications of their responses for the price-earnings relation. I do not find evidence of informed trading among these investors. Changes in their holdings also do not resemble random, uncorrelated noise trading. Instead I find that the number of retail investors holding a firm's shares increases in response to both more positive and more negative earnings news, consistent with attention-driven trade. While retail trades appear to react to announced earnings, an analysis of intraday trading indicates that these traders respond most consistently to market returns following the earnings announcement, as opposed to only earnings itself. Consistent with this coordinated trading exerting pressure on prices, I find that stock returns drift upward following both the most positive and the most negative earnings surprises when increases in retail holdings are greatest and the firm is relatively small or costly to sell short.

Keywords Retail investor · Individual investor · Robinhood · Earnings announcement · Post-earnings-announcement drift

JEL Classification G10 · G11 · G12 · G14 · G24 · G41 · G50 · M41 · O33

1 Introduction

Retail investors are becoming increasingly active traders, a phenomenon that has captured the attention of the media, regulators, and the firms whose shares are traded (Osipovich 2020; Phillips 2021; U.S. Securities and Exchange Commission [SEC] 2021). In several well-publicized instances, surges in retail investor trading have corresponded to wild fluctuations in firms' stock prices—fluctuations seemingly divorced from fundamental firm performance (McCabe 2021). Such episodes raise

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the question of how retail investors affect stock prices and market quality, a question unresolved by the literature. Early empirical work finds that these investors can distort markets, with attention-driven retail trade exerting price pressure on stocks (Aboody et al. 2010; Barber et al. 2009; Hvidkjaer 2008). In contrast, later studies highlight that retail investors can enhance market quality through either increased liquidity (Blankespoor et al. 2018; Kaniel et al. 2008), informed trade (Farrell et al. 2022), or both (Kaniel et al. 2012; Kelley and Tetlock 2013). These conflicting findings may stem from heterogeneity among retail investors (Blankespoor et al. 2020; Dorn et al. 2008; Eaton et al. 2022; Fong et al. 2014). New technologies and reduced trading costs in recent periods likely contribute to changes in the demographics and behavior of retail traders (van der Beck and Jaunin 2023; Welch 2022).

I contribute to this literature by showing how a particular subset of contemporary retail investors responds to accounting information and the associated effects on the pricing of earnings. I measure retail investor activity with the number of Robinhood investors holding a firm's shares. Robinhood is a financial services company that provides commission-free trading primarily via a mobile app. Evidence suggests Robinhood investors are inexperienced (Eaton et al. 2022), with Robinhood's CEO indicating 50% of its users identify as first-time investors (Testimony of Vladimir Tenev 2021). By focusing on Robinhood, I offer sharper inferences about a specific group of retail investors. These relatively inexperienced investors are likely the SEC's focus in its mission of investor protection. A longstanding SEC concern is that new investors are particularly susceptible to manipulation and fraud, with former SEC Chair Arthur Levitt (1998) noting that "many of [these] novice investors are our society's most vulnerable citizens." An advantage of my setting is I can focus on this subset of retail investors and offer refined inferences on how they trade. However, a limitation of my sample is it speaks only to the behavior of these particular investors, and I cannot contrast their behavior with that of other retail traders. Thus my results should be interpreted in the context of the broader literature on retail investors, which I discuss in Section 2.

I focus my analysis on the setting of earnings announcements for several reasons. First, earnings announcements are a primary source of information regarding firm performance (e.g., Beaver et al. 2018). Thus earnings announcements provide a powerful setting to test how Robinhood investors trade on or in anticipation of the release of public information related to fundamental firm performance. Second, earnings releases occur regularly and are highly visible, and expectations of upcoming earnings can be measured using analyst forecasts. All of these features facilitate the interpretation of investor reactions to earning news. Third, regulators focus on earnings announcements in their mission to provide equal, transparent, and open access to financial information.[1] Understanding how retail investors—and novices

[1] As examples of regulation prioritizing earnings releases, Regulation FD prohibits selective disclosure with an emphasis on eliminating the practice of managers privately communicating information regarding upcoming earnings (SEC 2000). Regulation G requires any non-GAAP earnings disclosure to include a reconciliation to GAAP earnings. And, in conjunction with Regulation G, the SEC adopted amendments requiring firms to file a Form 8-K for any earnings announcement, thus creating a "central depository where investors and other market participants can look to find the latest earning announcements and releases by public companies and provide enhanced attention to those announcements and releases" (SEC 2003).

in particular—interact with earnings releases can inform these regulatory efforts. Fourth, the academic literature has studied earnings announcements extensively, allowing my results to be interpreted in the context of this larger literature.

I test competing predictions of how retail investor trade relates to market efficiency. On the one hand, retail traders can improve market quality by executing informed trades or providing liquidity to other investors. On the other hand, they can distort prices through attention-based trading. If retail investors make informed trades, I expect to observe a positive association between changes in user holdings and earnings news. Retail investors providing liquidity to other investors predicts a negative association between changes in retail holdings and earnings news. Either informed trade or liquidity provision would facilitate a more complete initial market response to earnings announcements and thus predict less post-earnings announcement price revision. Conversely, if retail investors engage in attention trade and respond primarily to the visibility of earnings events, then I expect more extreme earnings news, both negative and positive, to predict greater increases in user holdings. This attention trade can also exert pressure on prices.

My results indicate that Robinhood investors engage in attention-driven trade, with the number of Robinhood investors holding a stock increasing following both negative and positive earnings news.[2] These results hold whether I measure earnings news as reported earnings relative to analyst expectations or as the abnormal market return on the earnings announcement date. In contrast to earlier work, I do not find consistent evidence that retail investors react to earnings surprises measured using expectations from a seasonal random walk model (e.g., Battalio and Mendenhall 2005). This finding suggests that contemporary Robinhood investors find analyst-based earnings expectations more salient than retail investors examined previously, perhaps because the Robinhood app highlights earnings relative to analyst forecasts (Moss 2022) or because media services have increasingly disseminated analysts' expectations in recent years (Blankespoor et al. 2018).

I leverage the intraday frequency of the Robinhood data to show these investors respond to stock returns following the earnings announcement, as opposed to only reacting to earnings news itself. In my sample, firms almost always announce earnings outside of trading hours (98.5% of the time). Investors who immediately react to earnings should trade early once the market opens. Investors who instead react to observed returns may respond with delay. I find some evidence that Robinhood user holdings move in the direction of earnings news upon the opening of the trading day following the earnings announcement. However, I find stronger evidence that intraday changes in Robinhood users are positively associated with more extreme prior intraday returns. Overall the results consistently support the inference that Robinhood investors react to the visibility of extreme returns driven by earnings events, although I find some evidence these investors also respond to the underlying earnings release.

[2] A limitation of my data source is that I can only observe the number of Robinhood users holding shares in a given firm. I cannot observe changes in the number of shares held. As detailed in Section 3, I refer to the number of users holding a firm's shares with terminology such as "user holdings," "Robinhood users," or "investor base."

In contrast to some prior work (e.g., Kaniel et al. 2012), I find no evidence retail investors in my sample make informed trades. However, while their trades appear uninformed, they also do not resemble random, uncorrelated noise trading (e.g., Kyle 1985). Instead, as noted above, Robinhood investors collectively respond to both positive and negative earnings surprises by taking positions in these stocks. Consistent with their trading exerting pressure on prices, I find that the immediate market response per unit of earnings surprises (the earnings response coefficient or ERC) is more positive when the retail investor base increases during the earnings announcement window, a result driven by positive earnings surprises. This result should be interpreted with caution, however, as it could reflect Robinhood investors being attracted to firms with more extreme returns.

I also find evidence consistent with price pressure when examining the evolution of returns following the earnings announcement. Specifically, I find that returns drift upward for both the most positive and the most negative earnings surprises for stocks with the largest increase in Robinhood investors during the earnings announcement. These results again suggest attention-driven trading and contrast with the traditional post-earnings announcement drift (PEAD; Bernard and Thomas 1989), where returns drift in the direction of the earnings surprise (i.e., returns drift downward for the most negative earnings surprises). These results are concentrated among smaller firms. For larger firms, any effect of retail trade on share price appears to dissipate quickly. Consistent with returns being more sensitive to retail buying when arbitrage costs are high (e.g., Kumar and Lee 2006), I document that the upward drift for firms with increases in Robinhood users is greatest when short-selling costs are high.

Overall I show that novice retail investors take positions in firms announcing more extreme earnings and that these greater retail holdings are associated with more positive returns following the earnings announcement for both negative and positive earnings surprises. These investors appear to respond more consistently to market returns following the earnings announcement, relative to the earnings news itself. These findings echo such studies as the work of Barber and Odean (2008), who find attention-trading in response to extreme prior-day returns, and Blankespoor et al. (2019), who show retail investors trade in response to trailing returns featured in media coverage of earnings announcements rather than the earnings information itself. However, my findings contrast with other work showing retail investors can contribute to market efficiency through informed trading and liquidity provision (e.g., Kaniel et al. 2012; Kelley and Tetlock 2013). My results are likely a product of the subset of investors on which I focus. Mixed prior findings may stem from heterogeneity among retail investors. Robinhood investors appear to represent the type of investor driving the current surge in retail trade. However, the types of information these investors rely on may differ from the types used by other traders. Thus, while my sample allows for refined inferences on a subset of traders, my results may not extend broadly across the spectrum of all retail investors.

While my analysis relies on Robinhood data, it speaks more broadly for the activity of a new generation of novice traders, regardless of their trading venue. The proliferation of trading apps, such as Webull, M1 Finance, and moomoo, highlights a trend in retail investing toward low-cost, mobile-centric trading venues that seems likely to persist beyond the popularity of Robinhood itself. Further, more traditional brokerages (TD Ameritrade, Fidelity, E-Trade, JP Morgan, Vanguard) have followed Robinhood and eliminated trading commissions, likely broadening their appeal to inexperienced investors (Beilfuss 2019; Beilfuss and Osipovich 2019). Thus trade by retail investors seems likely to continue to grow. And even though retail investors hold a relatively small proportion of the total stock market, they can have an outsized effect on stock returns, due to the inelastic demand of institutional shareholders, whose trading increasingly follows passive indexing strategies. For example, van der Beck and Jaunin (2023) estimate that, while Robinhood investors hold only 0.15% of the aggregate equity market, they can account for as much as 10% of the variation in stock returns, highlighting the growing importance of these investors in affecting market outcomes.

2 Prior literature and hypothesis development

In this section, I first review prior work on retail investors. Second, I discuss the paper relative to other research examining Robinhood investors. Third, I synthesize the predictions motivated by prior literature into formal hypotheses. These hypotheses aim to differentiate whether Robinhood investors engage in information-based trade, liquidity provision, or attention-driven trade.

2.1 Retail investors literature

A principal challenge in research on retail investors is identifying their trading activity. As a result, many studies in this area use proprietary datasets. An implication of this is that studies in this area are not directly comparable, as each sample likely captures a different dimension of the larger population of retail traders. Papers' samples are often also drawn from different time periods, which may also contribute to disparate results.

For example, Barber and Odean (2008) find retail investors make relatively naïve investment decisions, buying stocks that grab their attention. In contrast, Kaniel et al. (2008), Kaniel et al. (2012), and Kelley and Tetlock (2013) find evidence of both informed trading and trading motivated by liquidity provision among retail investors. These seemingly conflicting results may stem in part from differences in the papers' samples. Barber and Odean (2008) base their analysis on data from three brokerage firms in a sample period spanning 1991 to 1999. In contrast, Kaniel et al. (2008) and Kaniel et al. (2012) use data on orders executed on the New York Stock Exchange (NYSE) from 2000 to 2004, while Kelley and Tetlock's (2013) sample comes from a wholesaler and covers the years 2003 to 2007. Thus differences in results could be attributed to differences in sample periods, as the market conditions of the late 1990s could have attracted a different investing clientele than those of the early 2000s.

Further, different proprietary data sources could be biased toward different demographics of retail traders. Battalio and Loughran (2008) argue brokers are incentivized to fulfill orders they perceive as uninformed from their own inventory or sell these orders to intermediaries. These parties are eager to fulfill these orders and earn the bid-ask spread, as adverse selection costs associated with informed trading are less of a concern. More informed orders may instead be routed to exchanges. Thus the venue where an order is fulfilled may be associated with the sophistication of the individual submitting the order.

The literature also uses several broader measures of retail trading that do not rely on proprietary data. However, these measures also have limitations. Early studies often used trade size to proxy for retail investors (e.g., Barber et al. 2009). However, with the advent of algorithmic trading and order-splitting, measures based on trade size are unlikely to reliably identify retail trading (e.g., Cready et al. 2014). More recently, Boehmer et al. (2021) propose a measure that identifies and signs (i.e., classifies as a buy or a sell order) retail orders based on how the order is executed and the amount of price improvement given to the order. Friedman and Zeng (2023) use this measure to document that retail trading is associated with higher ERCs and PEAD, which they interpret as consistent with these traders providing liquidity to informed investors.[3] While the Boehmer et al. (2021) measure has many advantages, it is limited in that it identifies only market orders (i.e., not limit orders) executed off-exchange. As argued in the previous paragraph, brokers likely strategically route orders, resulting in a nonrandom subset of retail orders being routed off-exchange. Further, Barardehi et al. (2023) argue demand from institutional traders also contributes to the internalization decision, and thus the measure may partially reflect institutional demand. Finally, Barber et al. (2023) demonstrate the Boehmer et al. (2021) algorithm performs less effectively for wider bid-ask spreads and is therefore less reliable in recent periods. Specifically, using retail orders submitted from late 2021 to mid-2022, they demonstrate the measure recognizes about one-third of their trades as retail trades and correctly classifies trades as buys or sells 72% of the time.[4]

In sum, precisely identifying retail trade is difficult. Many highly cited papers rely on proprietary datasets that are now several decades old. With the composition of the population of retail investors evolving, prior inferences may no longer hold. While the recent increase in retail investor activity has parallels to the rise in trading associated with the advent of online brokerages in the 1990s (e.g., Choi et al. 2002), evidence suggests that traders who transitioned online during the 1990s were relatively experienced and wealthy (Barber and Odean 2002). In contrast, recent evidence suggests inexperienced, first-time investors have driven the current surge in retail investing (Barber et al. 2022; Testimony of Vladimir Tenev, 2021). By using data from Robinhood, I can better identify a contemporary sample of novice retail investors. As argued in the introduction, understanding these investors' trading and how they respond to accounting releases can help inform policies aimed at protecting retail traders.

[3] Unlike Friedman and Zeng (2023), I differentiate between positive and negative earnings news to examine the potential of attention-driven trading by Robinhood investors.

[4] Barber et al. (2023) propose an alternative trade classification scheme based on the midpoint of the bid-ask spread.

2.2 Robinhood literature

Several recent works examine the same trading data from Robinhood that I use. Welch (2022) examines general trading patterns and preferences of Robinhood investors. He finds Robinhood users prefer stocks with high trading volume and those of firms with familiar products or services. Moss et al. (2023) also examine Robinhood users' preferences, specifically their preference for environmental, social, and governance (ESG) activities. They find no evidence that Robinhood investors respond to ESG-related disclosures, in contrast to experimental evidence showing other individuals value these activities (Martin and Moser 2016). While these papers offer evidence on the general preferences of Robinhood investors, my study focuses on how these investors trade and price a specific and regulated firm disclosure, accounting earnings.

Other papers emphasize understanding how Robinhood's app design and content curation practices influence investors. Moss (2022) shows that push notifications from the Robinhood app to investors induce trading. He further shows that Robinhood investors respond to earnings information as displayed by Robinhood. Barber et al. (2022) also find features of the Robinhood app influence investor behavior. As I do, they conclude that Robinhood investors engage in attention trading and show that the app contributes to this behavior by highlighting stocks with large absolute returns (i.e., top movers). These papers advance the understanding of how the content curation practices of information intermediaries influence trading. I also examine the determinants of Robinhood investors' trading but with an emphasis on understanding to which external signals they respond (i.e., earnings or returns). In addition, my study explores the outcomes of this trade, namely, how it affects the price-earnings relation.

Finally, several papers examine how Robinhood traders impact market quality. Van der Beck and Jaunin (2023) and Pagano et al. (2021) examine how Robinhood investors trade during the COVID-19 pandemic and the associated stock market effects. Pagano et al. (2021) find Robinhood users' holdings are generally associated with improved market quality (i.e., lower spreads and smaller order imbalances). However, they also find evidence this association attenuates or even reverses early in the pandemic period. In contrast, van der Beck and Jaunin (2023) show that Robinhood investors moderate price declines early in the pandemic by supplying liquidity and contribute to the market recovery in the second quarter of 2020. Welch (2022) also finds a stabilizing effect of Robinhood investors early in the pandemic. However, Eaton et al. (2022) find evidence that Robinhood activity is associated with worse market quality. Specifically, they find Robinhood outages coincide with reduced market order imbalances, increased liquidity, and lower volatility. My paper complements these studies focusing on market quality by offering evidence of how Robinhood investors contribute to or detract from the efficiency with which market prices reflect accounting earnings.

2.3 Hypotheses development

In this section, I develop hypotheses for how Robinhood investors will trade around earnings announcements and the implications of this trade for the price-earnings relation. The literature suggests retail investors may engage in informed trading, liquidity provision, or attention-induced trading. The following hypotheses discriminate between these different descriptions of retail investor behavior.

Retail investors can help prices incorporate earnings information either by trading on earnings news directly or by providing liquidity to other investors. On the earnings announcement day, if retail investors trade on revealed earnings news, they will likely trade in the direction of the earnings surprise, as they update their demand for the firm's shares based on their revised expectations of future cash flows (e.g., Battalio and Mendenhall 2005). If these investors instead provide liquidity to other traders who trade on earnings news, then they will trade contrary to the direction of earnings surprises.[5] That is, other investors trading on the earnings news demand immediacy, and retail investors provide liquidity by taking the other side of these trades (Barrot et al. 2016; Grossman and Miller 1988; Kaniel et al. 2008; Kelley and Tetlock 2013).[6]

Alternatively, investors may engage in attention-driven trade. In this case, more extreme earnings news, both positive and negative, would prompt more buying (Barber and Odean 2008; Hirshleifer et al. 2008; Lee 1992). Under the attention-trade hypothesis, more visible information events (i.e., more extreme earnings surprises) attract investors' attention. Due to limited attention, investors are aware of only a subset of firms (Merton 1987). A high visibility event attracts their attention, bringing a firm into their investment opportunity set and increasing the likelihood the investor will purchase the firm's shares. One could also conceptualize attention traders as investors who misinterpret visibility as information (e.g., Black 1986; De Long et al. 1990). While attention could also induce selling, it tends to asymmetrically induce buying. Due to short-sale constraints, retail investors typically sell only shares of firms they already own. Thus a high-attention event will cause many investors to consider buying, but only a smaller subset of investors who already own shares will consider selling (Barber and Odean 2008; Gervais et al. 2001; Lee 1992). The following hypotheses summarize the preceding discussion:

> *H1a: If Robinhood investors trade in response to earnings news (provide liquidity at the earnings announcement), then there will be a positive (negative) association between earnings news and changes in Robinhood user holdings at the earnings announcement.*
>
> *H1b: If Robinhood investors trade in response to the visibility of the earnings announcement, then the most extreme positive and negative earnings news will be associated with increases in Robinhood user holdings at the earnings announcement.*

Further, if Robinhood investors make informed trades and have private information regarding an upcoming earnings realization, then they should trade in the

[5] News contrarian trading following the earnings announcement could also align with profit-taking (Kaniel et al. 2012). However, this would presume that the pre-announcement trading is in the same direction as the earnings surprise. I find instead that retail trade negatively predicts earnings news.

[6] Trading motivated by "liquidity provision" (e.g., Barrot et al. 2016) is distinct from "liquidity trading." Traders providing liquidity play the role of a market maker, responding to other traders' demands. Liquidity trading reflects a demand for liquidity, which may occur for idiosyncratic reasons (e.g., Glosten and Milgrom 1985).

direction of the upcoming earnings surprise. Increases in user holdings in advance of positive earnings surprises and decreases in user holdings preceding negative earnings surprises would be consistent with informed trade (e.g., Boehmer et al. 2021; Chen et al. 2014; Kaniel et al. 2012; Kelley and Tetlock 2013). Therefore, in addition to the associations predicted in H1a, I provide further evidence on the possibility of informed trading by examining the association between earnings news and prior changes in user holdings in Section 4.1.

Next I turn to how retail trading influences the price-earnings relation. Classical work views individual investors as noise traders who do not trade on news related to fundamental performance but instead trade for idiosyncratic reasons. This noise trading can contribute to market quality by providing camouflage to sophisticated investors (Glosten and Milgrom 1985; Kyle 1985). More noise trade allows informed investors to trade more aggressively on their private information, which in turn encourages these investors to acquire information. Under this model, additional retail trading facilitates a more complete initial market response to the earnings announcement. This will manifest in a larger ERC and less post-earnings announcement price revision (i.e., PEAD). A similar pattern would be expected if retail investors were to make informed trades at the earnings announcement. More informed trading would result in a more complete initial response to the earnings news and less post-earnings price revision (e.g., Ng et al. 2008). Evidence on how retail investors influence price discovery around the earnings announcement is mixed. While Hirshleifer et al. (2008) do not find evidence that retail investors contribute to the market's underreaction to earnings, other studies show that more sophisticated investors can facilitate price discovery (e.g., Bartov et al. 2000; Ke and Ramalingegowda 2005). Again the heterogeneous and changing composition of the population of retail investors may contribute to these mixed results.

Instead of facilitating price discovery, coordinated attention trade driven by the earnings announcement could exert pressure on prices. When prices do not immediately revert to fundamental value, betting against retail investors is risky, as it may become necessary to liquidate one's position before prices correct (De Long et al. 1990). Thus, if more extreme earnings surprises prompt coordinated purchasing from retail traders, then returns in response to these more extreme earnings surprises—both positive and negative—will be more positive. How this will manifest in the ERC is more nuanced: more positive returns following positive earnings surprises will result in larger ERCs, but more positive returns following negative earnings surprises will attenuate ERCs.[7] These predictions highlight that ERCs may vary with the sophistication of a firm's traders, in addition to more traditional determinants of ERCs, such as earnings persistence, firm risk, and growth opportunities (Kothari 2001).

[7] Further complicating the interpretation of the relationship between retail trading and ERCs is the fact that retail investors both contribute and respond to returns at the earnings announcement. Thus more extreme negative earnings surprises may prompt more retail purchases, which in turn puts upward pressure on prices. These simultaneous, countervailing effects are discussed in the context of the results in Section 4.4.

The above discussion highlights that larger ERCs may represent either a more complete reaction or an overreaction to the earnings release. While a larger ERC followed by minimal drift is consistent with a more complete initial reaction (Blankespoor et al. 2020), a larger ERC followed by drift in the same direction as the initial return is more consistent with a longer-term overreaction. Eventually, prices should revert to fundamental value, but the timing of this reversal is unclear.[8] Finally, a larger ERC followed by drift in the opposite direction of the return at the earnings announcement is consistent with an initial overreaction and subsequent correction. Thus it is important to interpret the ERC together with the trajectory of prices following the earnings announcement. If attention-drive trade by retail investors continues to exert upward pressure on prices following more extreme earnings surprises, returns will continue to drift upward (Barber et al. 2009; Dorn et al. 2008). Further, sophisticated traders seeking to exploit predictable returns stemming from attention-induced buying can contribute to return continuation (Barberis and Shleifer 2003). In sum:

H2a: If Robinhood trade facilitates or represents more informed trading at the earnings announcement, then increases in Robinhood user holdings will be associated with larger ERCs at the earnings announcement and less price revision following the earnings announcement.
H2b: If Robinhood trade represents attention trade at the earnings announcement, then increases in Robinhood user holdings will be associated with larger ERCs for the most positive earnings surprises and smaller ERCs for the most negative earnings surprises. Further, there will be a positive drift in returns following both the most positive and the most negative earnings surprises.

Finally, to the extent attention-induced trade by Robinhood investors puts pressure on prices, this effect should strengthen when market frictions prevent arbitrage.

3 Research setting and data

Robinhood published data on the number of Robinhood users holding a particular stock at a moment in time until August 2020. The website Robintrack archived this data from May 2, 2018, to August 13, 2020.[9] The data contains snapshots at roughly one-hour intervals of the number of users who hold a particular stock. I take the number of users from the last reading for a given day in my primary analysis. For example, my data show that 62,391 users held Hertz (HTZ) on June 1, 2020. In some analyses, I examine intraday changes in the number of users holding a stock, as discussed below.

A limitation of this data is that I observe only the number of users holding a firm's shares. The data will not capture changes in ownership by Robinhood users

[8] In the research design, described in Section 4.5, I take a flexible approach that measures post-earnings drift in returns allowing for both overreactions and reversals (e.g., Blankespoor et al. 2018).

[9] https://robintrack.net/

if these investors add to an existing position by purchasing additional shares or sell shares without completely closing a position. The literature presents some evidence that retail investors are likely to entirely close positions when selling. Namely, results from Odean (1998) indicate that investors from a discount brokerage fully exit a position when selling shares 79% of the time.[10] Throughout the paper, I refer to the number of users holding a firm's shares with phrases such as "users holdings," "Robinhood users," or "investor base." Any reference to trading by Robinhood users should be interpreted as capturing net changes in the number of users holding a firm's shares.

My analyses focus on quarterly earnings announcements. I calculate the change in the number of Robinhood users during a firm's earnings announcement (*Δ-Users*) as the difference between the number of users holding the stock at the end of the earnings announcement date and the number of users holding the stock one day before the earnings announcement. As firms in my sample almost always announce earnings outside of trading hours (98.5% of the time), this represents the change in users over the trading day immediately following the announcement of earnings. I scale this difference by the average number of users holding the stock during the window beginning 65 trading days before the earnings announcement and ending two trading days before the earnings announcement. I adjust the earnings announcement date to the next trading day if a firm announces earnings after trading hours. In some analyses, I decompose *Δ-Users* into its intraday components and measure the change in users over hourly intervals on the earnings announcement date. Finally, I also calculate the change in users over the quarter preceding the earnings announcement, *Δ-Users, Prior*, as the number of users holding a stock two trading days before the earnings announcement less the number of users holding a stock 65 trading days before the earnings announcement, scaled by the average number of users during this time. As discussed below, I use decile ranks of these variables in the analyses.

At the earnings announcement, I measure earnings news in several ways. First, like most research, I measure earnings surprises using analyst forecast errors (*AFE*), defined as actual quarterly earnings per share (EPS) less the median analyst forecast of EPS, scaled by the firm's share price at the end of the fiscal quarter. Second, since retail investors may have more naïve earnings expectations (Battalio and Mendenhall 2005) or may not rely on analyst forecasts, due to forecast biases relating to analysts' conflicts of interest (Jame et al. 2016), I also measure earnings surprise relative to a forecast based on a seasonal random walk. This measure, *SRWFE*, is defined as actual EPS less EPS from the same fiscal quarter of the prior year, scaled by price. Last, I use the market-adjusted abnormal return, *Abn. Ret.*, as a measure of earnings news. Retail investors may find earnings news reflected in EPS too difficult to process into an informed assessment of firm value and thus choose to learn from price instead (e.g., Grossman and Stiglitz 1980). For *AFE*, I use actual and forecasted earnings from the Institutional Brokers' Estimate System (IBES). For *SRWFE*, I use EPS data from Compustat. I use return and price data from the Center for Research in Security Prices (CRSP). In some analyses, I decompose the return on the earnings

[10] Contrast the sample sizes for Tables II and IV in Odean (1998).

Table 1 Tabulations of Key Variables

Panel A: Means of Key Variables by Decile

Decile:	*Abn. Ret*	*Δ-Users*	*AFE*	*SRWFE*
1	-0.17	-0.11	-0.10	-0.39
2	-0.08	-0.03	-0.01	-0.02
3	-0.04	-0.01	-0.00	-0.01
4	-0.02	-0.01	-0.00	-0.00
5	-0.01	-0.00	0.00	-0.00
6	0.01	0.00	0.00	0.00
7	0.02	0.01	0.00	0.00
8	0.04	0.02	0.00	0.01
9	0.07	0.06	0.01	0.02
10	0.18	0.67	0.07	0.52
Total	0.00	0.06	-0.00	0.01

Panel B: Means of Key Variables by Tercile

Tercile:	*Abn. Ret*	*Δ-Users*	*AFE*	*SRWFE*
1	-0.09	-0.05	-0.03	-0.12
2	0.00	0.00	0.00	0.00
3	0.09	0.23	0.02	0.16
Total	0.00	0.06	-0.00	0.01

All variable definitions are given in Appendix A. The analyses use decile ranks of *Δ-Users*, *AFE*, and *SRWFE*, ranging from – 0.5 to 0.5 (i.e., decile ranks from 0 to 1 and then subtract 0.5 so the hypothetical median takes a value of zero)

announcement date into hourly intraday returns using price data from NYSE Trades and Quotes (TAQ). Finally, in analyses examining longer horizon returns, I calculate cumulative abnormal returns (CARs) over the 50 trading days following the earnings announcement. This research design is detailed in the following section.

Table 1 tabulates the means of *Abn. Ret.*, *Δ-Users*, *AFE*, and *SRWFE*. Panel A does this by decile and panel B by tercile of each variable. To address outliers and potential nonlinearities, I follow prior work and use ranks of these variables in the later analyses (Livnat and Mendenhall 2006). Specifically, I rank *Δ-Users*, *AFE*, and *SRWFE* into deciles and then scale the ranks to range from 0 to 1. Then I subtract 0.5 so that the final variables range from – 0.5 to 0.5, with the hypothetical median observation taking a value of zero.

In other analyses, I use indicators for *Abn. Ret.*, *AFE*, and *SRWFE* being in their lowest or highest tercile. Specifically, *High Abn. Ret.*, *High AFE*, and *High SRWFE* indicate the observation is in the highest tercile of the corresponding variable. I similarly define *Low Abn. Ret.*, *Low AFE*, and *Low SRWFE* for the lowest terciles. Panel B of Table 1 indicates that the mean of each of these variables is positive in the highest tercile, negative in the lowest tercile, and near zero in the middle tercile.

I use several control variables to measure factors that likely relate to earnings, returns at the earnings announcement, and retail trading. Namely, I control for firm size, growth opportunities, risk, and leverage (Collins and Kothari 1989). *Size* is the logarithm of the market value of equity (*MVE*). *MTB* is *MVE* divided by the book

Table 2 Summary Statistics

	Count	Mean	Std. Dev	p25	Median	p75
Abn. Ret	22,299	0.00	0.10	-0.04	0.00	0.04
Δ-Users	22,299	0.06	0.59	-0.01	0.00	0.02
AFE	22,299	-0.00	0.19	-0.00	0.00	0.00
SRWFE	22,299	0.01	1.15	-0.01	0.00	0.01
Size	22,299	21.00	2.02	19.62	21.04	22.33
MTB	22,299	3.51	7.45	1.15	2.11	4.36
Persistence	22,299	0.29	0.32	0.05	0.26	0.53
Ln(Analysts)	22,299	1.96	0.72	1.39	1.95	2.48
Volatility	22,299	0.03	0.02	0.02	0.03	0.04
Avg. Turnover	22,299	0.01	0.01	0.00	0.01	0.01
Beta	22,299	1.08	0.44	0.80	1.07	1.35
Leverage	22,299	0.83	2.75	0.13	0.55	1.20
Loss	22,299	0.37	0.48	0.00	0.00	1.00
Special	22,291	0.11	0.31	0.00	0.00	0.00

All variable definitions are given in Appendix A. The analyses use decile ranks of *Δ-Users*, *AFE*, and *SRWFE*, ranging from – 0.5 to 0.5 (i.e., decile ranks from 0 to 1 and then subtract 0.5 so the hypothetical median takes a value of zero)

value of equity. *Beta* is the coefficient from regressing daily firm return less the risk-free rate on market returns less the risk-free rate over the 252 trading days ending three trading days before the earnings announcement. *Leverage* is total debt divided by the book value of equity. *Persistence* is the coefficient of EPS regressed on lagged EPS within firm, using up to 10 years of data. I also include an indicator, *Loss*, which takes a value of one if EPS is negative and zero otherwise. Further, *Ln(Analysts)* is the logarithm of the number of analysts contributing to the earnings forecast I use to calculate *AFE*. *Volatility* is the standard deviation of daily returns over the period beginning 65 trading days before the earnings announcement and ending two days prior, and *Avg. Turnover* is the average daily volume divided by shares outstanding during the same period. I winsorize continuous variables at the first and 99th percentiles.

In summary, the sample is the intersection of stocks in the Robintrack data, common stocks on CRSP, IBES, and Compustat. Some analyses examining intraday returns further require data from TAQ. Table 2 gives summary statistics. Appendix A provides all variable definitions.

4 Analysis and results

This section describes my analyses and results. First, I examine whether retail trade pre-earnings announcement predicts earnings news on the announcement date. Second, I examine the determinants of retail investor trading on the earnings announcement date. Third, I describe how ERCs vary with retail investor trading. Finally, I show how retail trading at the earnings announcement relates to future returns.

4.1 Predicting earnings news using pre-announcement retail investor trading

If retail investors trade on private information of upcoming earnings, then their trading pre-announcement should be in the direction of the news revealed on the earnings announcement date. To examine this possibility, I alternately regress two measures of earnings news, *AFE* and *Abn. Ret.*, on *Δ-Users, Prior*, and controls. If retail investors trade in the direction of earnings news before the earnings announcement, the coefficient on *Δ-Users, Prior* will be positive in the regression. In this and all regressions, I include firm and quarter-year fixed effects and cluster standard errors by firm.

Table 3 gives the results of this analysis. The results are inconsistent with the premise of informed retail trade underlying hypothesis H1a. Specifically, *Δ-Users, Prior* is not positively associated with either *AFE* or *Abn. Ret*. Instead both measures of earnings announcement news have a negative and marginally significant association with *Δ-Users, Prior*.

Table 3 Predicting Earnings Surprises Using Prior Changes in Robinhood Users

	(1)	(2)
Dependent variable =	*AFE*	*Abn. Ret*
Δ-Users, Prior	-0.014*	-0.005*
	(-1.76)	(-1.85)
Size	-0.025***	-0.045***
	(-2.86)	(-13.73)
MTB	-0.001	-0.000
	(-1.34)	(-1.23)
Persistence	-0.046**	-0.008
	(-2.16)	(-1.39)
Ln(Analysts)	0.002	0.005
	(0.10)	(1.07)
Volatility	0.091	-0.106
	(0.31)	(-1.09)
Avg. Turnover	-1.536***	0.011
	(-3.24)	(0.07)
Adj. R-Sq	0.154	0.059
N	22,254	22,254

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ (for two-tailed tests, t-stats in parentheses)

Firm and quarter-year fixed effects included. Standard errors clustered by firm. *AFE* is actual quarterly earnings per share less the median analyst forecast, scaled by price. *Abn. Ret.* is the market-adjusted abnormal return on the earnings announcement date. *Δ-Users, Prior* is the number of users holding a stock two trading days before the earnings announcement less the number of users holding a stock 65 trading days before the earnings announcement, scaled by the average number of users during this time. The analyses use decile ranks of *AFE* and *Δ-Users*, *Prior*, ranging from −0.5 to 0.5 (i.e., decile ranks from 0 to 1 and then subtract 0.5 so the hypothetical median takes a value of zero). Full variable definitions are given in Appendix A

4.2 Retail investor trading at the earnings announcement

Next I more directly test hypothesis H1 by examining which signals retail investors respond to at the earnings announcement. Hypothesis H1a predicts associations consistent with retail investors responding to the information content of these signals or providing liquidity, while H1b predicts these investors instead respond to the visibility of stocks at the earnings announcement.

For these tests, I regress changes in retail investors' holdings, or *Δ-Users*, on my measures of earnings news: *AFE*, *SRWFE*, and *Abn. Ret*. Panel A of Table 4 provides the results. In the first column, the coefficient on *AFE* is positive and significant, consistent with retail investors trading in the direction of earnings surprises. This initial evidence favors H1a and suggests Robinhood investors update their assessments of firm value and demand for a firm's shares based on the earnings surprise (Battalio and Mendenhall 2005). However, unlike Battalio and Mendenhall (2005), I do not find a significant association between *SRWFE* and retail trade at the earnings announcement in column (2). This result suggests that analyst forecasts may have become more salient for retail traders in my sample, relative to those examined by prior work.

In contrast to the positive association between *Δ-Users* and *AFE* in column (1), I find a significantly negative association between *Abn. Ret.* and *Δ-Users* in column (3). This type of return contrarian trade also aligns with H1a but suggests liquidity provision (Kaniel et al. 2008). However, the inconsistent results in panel A of Table 4 may also stem from model misspecification. In particular, if retail investors respond to the visibility of extreme earnings events (e.g., Barber and Odean 2008), then the association between retail trading and earnings news will not be linear. Instead retail investors would increase their positions in response to both positive and negative earnings events.

Panel B of Table 4 investigates this possibility. To allow the associations between *Δ-Users* and the earnings news variables of *AFE*, *SRWFE*, and *Abn. Ret.* to vary depending on the sign of the earnings news, I include indicator variables for each of these variables being in their highest or lowest terciles. For example, *Low AFE* indicates that *AFE* is in the lowest tercile of *AFE*. Note *AFE* is negative in the *Low AFE* tercile. *High AFE* indicates the highest tercile of *AFE.* I omit an indicator for the middle tercile of *AFE*. Thus the coefficients on *Low AFE* and *High AFE* can be interpreted as the incremental effect on *Δ-Users* when *AFE* is in either the lowest or highest tercile, relative to the middle tercile. I similarly define *High* and *Low* indicators for *SRWFE* and *Abn. Ret.*

The results of these analyses support H1b, documenting an increase in the number of Robinhood investors holding a firm's shares in response to both more negative and more positive earnings news. Specifically, panel B of Table 4 shows that the coefficients on both *Low AFE* and *High AFE* in column (1) are significantly greater than zero. Similarly, in column (3), both *Low Abn. Ret.* and *High Abn. Ret.* have significantly positive coefficients. In column (2), I again find no evidence that Robinhood investors react to *SRWFE*. The associations between *Δ-Users* and the earnings news measures are strongest when measuring earnings news with market returns. In column (4), which includes all the earnings news measures together, the coefficient

Table 4 Change in Robinhood Users and Earnings News

Panel A: Earnings Surprises and Announcement Returns

	(1)	**(2)**	**(3)**	**(4)**
AFE	0.029***			0.071***
	(3.74)			(8.72)
SRWFE		0.001		0.002
		(0.08)		(0.28)
Abn. Ret			-0.432***	-0.490***
			(-11.61)	(-12.31)
Size	-0.014**	-0.015**	-0.037***	-0.036***
	(-2.00)	(-2.19)	(-5.24)	(-5.18)
MTB	0.001*	0.001*	0.001	0.001
	(1.78)	(1.73)	(1.54)	(1.63)
Loss	0.014*	0.009	-0.006	0.005
	(1.95)	(1.20)	(-0.90)	(0.66)
Ln(Analysts)	0.042***	0.042***	0.043***	0.044***
	(3.19)	(3.19)	(3.34)	(3.39)
Volatility	-0.449**	-0.443**	-0.485**	-0.500**
	(-2.01)	(-1.98)	(-2.14)	(-2.21)
Avg. Turnover	-0.999***	-1.038***	-1.022***	-0.927**
	(-2.71)	(-2.81)	(-2.68)	(-2.43)
Adj. R-Sq	0.095	0.094	0.110	0.114
N	22,299	22,299	22,299	22,299

Panel B: User Changes by Sign of Earnings News

	(1)	**(2)**	**(3)**	**(4)**
Low AFE	0.023***			-0.004
	(3.47)			(-0.64)
High AFE	0.043***			0.055***
	(6.08)			(8.04)
Low SRWFE		0.009		0.004
		(1.35)		(0.55)
High SRWFE		0.005		0.005
		(0.72)		(0.81)
Low Abn. Ret			0.191***	0.198***
			(32.57)	(33.76)
High Abn. Ret			0.058***	0.050***
			(10.09)	(8.72)
Controls	Yes	Yes	Yes	Yes
Adj. R-Sq	0.096	0.094	0.150	0.156
N	22,299	22,299	22,299	22,299

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ (for two-tailed tests, t-stats in parentheses)

Firm and quarter-year fixed effects included. Standard errors clustered by firm. The dependent variable in all models is *Δ-Users*, defined as the difference between the number of Robinhood users holding a stock at the end of the earnings announcement date and the number of users holding a stock one day

Table 4 (continued)

before the earnings announcement, scaled by the average number of users holding the stock during the window beginning 65 trading days before the earnings announcement and ending two trading days before the earnings announcement. *AFE* is analyst forecast error, defined as actual quarterly earnings per share (EPS) less the median analyst forecast of EPS, scaled by price. *SRWFE* is seasonal random walk forecast error, defined as actual quarterly EPS less actual EPS from the same fiscal quarter one year prior, scaled by price. The analyses in Panel A use decile ranks of *Δ-Users*, *AFE*, and *SRWFE*, ranging from − 0.5 to 0.5 (i.e., decile ranks from 0 to 1 and then subtract 0.5 so the hypothetical median takes a value of zero). In panel B, *Low AFE*, *Low SRWFE*, and *Low Abn. Ret.* indicate the lowest tercile of these variables. Likewise, *High AFE*, *High SRWFE*, and *High Abn. Ret.* indicate the highest tercile of these variables. Indicators for the middle terciles are omitted. Full variable definitions are given in Appendix A

on *Low AFE* becomes insignificant. However, the coefficients on both *Low Abn. Ret.* and *High Abn. Ret.* remain highly significant. The association between *Δ-Users* and *Low Abn. Ret.* is particularly strong, highlighting the importance of allowing the association between retail trading and earnings news to vary, depending on the sign of the earnings news. Overall the results of Table 4 are most consistent with H1b, suggesting the particular type of retail investor in my sample engages in attention-driven trade. Changes in Robinhood investors' holdings are most consistently associated with market returns at the earnings announcement, although changes in user holdings are also associated with earnings surprises measured relative to analyst expectations.[11]

4.3 Intraday retail investor trading

The results thus far indicate that changes in the number of Robinhood users who own shares in a particular firm during an earnings announcement are significantly and positively associated with more extreme earnings news, regardless of whether the news is positive or negative. Increases in Robinhood holdings are particularly associated with earnings news when I measure this news using abnormal returns on the earnings announcement date. However, the fact that returns and retail trading are measured contemporaneously complicates the interpretation of these associations. This simultaneity makes it unclear whether retail traders react to market returns or whether, driven by some other factor, their trading exerts pressure on prices. Note that simultaneity is less of a concern when interpreting the relation between earnings surprises and retail trading, as firms almost always announce earnings before markets open, either after hours on the prior day or before the market opens on the current day. In my sample, 98.5% of earnings announcements are made outside of trading hours.

I exploit the intraday nature of my data to help address this issue and decompose earnings announcement returns and *Δ-Users* on the earnings announcement date into intraday components. I divide the trading day into one-hour intervals since this is the frequency that the stock holdings of Robinhood users

[11] Blankespoor et al. (2019) similarly find retail investors respond to returns and not earnings; however, they examine market returns over the trailing 12 months.

are available. To calculate the intraday change in users, I take the number of users holding a firm's shares as of 10 am, 11 am, 12 pm, 1 pm, 2 pm, 3 pm, and 4 pm. I then subtract the number of users holding the firm's stock one hour prior. Similar to *Δ-Users*, I scale the intraday change in users by the average number of users holding the stock during the window beginning 65 trading days before the earnings announcement and ending two trading days before the earnings announcement. Then I rank the variable within each intraday window into deciles and scale the rankings to take values ranging from − 0.5 to 0.5. For the intraday analysis, I restrict the sample to the 98.5% of firms that announce earnings outside of trading hours, as indicated by IBES. I drop some additional observations due to the intraday data requirements.

For returns, I calculate the first intraday return as the return from the previous trading day's closing price to the price at 10 am on the earnings announcement date. Subsequent return intervals end at 11 am, 12 pm, 1 pm, 2 pm, 3 pm, and 4 pm on the earnings announcement date. For each return interval, I calculate the cumulative abnormal return from the previous trading day's closing price to the end of the current interval. I calculate abnormal returns by subtracting the intraday return on Vanguard's Total Stock Market Index Fund (VTI), which tracks the performance of the CRSP US Total Market Index. Similar to previous analyses, I then define the indicator variables, *Low Intraday Abn. Ret.* and *High Intraday Abn. Ret.*, to equal one when the associated returns are in the lowest or highest tercile of the sample, respectively. To calculate these variables, I rank the intraday abnormal return within each intraday window.

Table 5 gives the results of the intraday analyses. The dependent variable is the change in Robinhood users in the hour interval ending on the hour indicated in the column heading. In each regression, I lag returns by one hour. Again, this analysis restricts the sample to earnings announced outside trading hours. Thus both the earnings surprise and the intraday return precede the change in Robinhood users. Since returns are lagged, relative to the change in users, the first intraday window in column (1) examines the change in users from 10 to 11 am. The intraday return variables in this column are based on the return from the previous trading day's closing price to 10 am on the earnings announcement date. Each subsequent column increments the end of the intraday interval by one hour.

Similar to prior analyses, Table 5 shows that *High AFE* has a reliably positive and significant association with user changes. Interestingly, and in contrast to the results of panel B in Table 4, *Low AFE* has a *negative* and significant association with the change in users in the first intraday interval, as shown in the first column. However, the coefficient on *Low AFE* becomes significantly positive in the last intraday interval. These results suggest Robinhood investors trade in the direction of earnings news in the trading hours immediately following the release of earnings, consistent with H1a. Potentially, this reflects a different demographic of Robinhood investors being more active early in the trading day.

However, consistent with H1b, Table 5 also shows that both more negative and more positive abnormal returns are associated with an increase in the number of users holding a firm's shares. This association between more extreme returns and retail positions is significantly positive in every intraday window for negative

Table 5 Intraday Changes in Robinhood Users

	11am	12 pm	1 pm	2 pm	3 pm	4 pm
Low AFE	-0.036***	-0.004	0.006	0.003	0.010	0.015**
	(-4.26)	(-0.55)	(0.83)	(0.50)	(1.52)	(2.23)
High AFE	0.056***	0.043***	0.037***	0.031***	0.031***	0.024***
	(6.23)	(5.15)	(4.76)	(4.04)	(4.29)	(3.43)
Low SRWFE	0.000	0.002	-0.011	0.009	0.007	-0.008
	(0.03)	(0.26)	(-1.50)	(1.27)	(0.99)	(-1.19)
High SRWFE	0.007	-0.004	-0.004	-0.000	0.012*	-0.005
	(0.77)	(-0.52)	(-0.55)	(-0.06)	(1.77)	(-0.66)
Low Intrday Abn. Ret	0.084***	0.195***	0.206***	0.193***	0.193***	0.185***
	(11.24)	(27.17)	(32.34)	(30.30)	(31.81)	(29.93)
High Intraday Abn. Ret	0.007	0.068***	0.079***	0.068***	0.072***	0.061***
	(0.98)	(9.50)	(12.34)	(11.07)	(12.18)	(10.78)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-Sq	0.101	0.116	0.127	0.132	0.130	0.136
N	20,850	20,958	21,018	21,024	21,264	20,816

* $p<0.10$, ** $p<0.05$, *** $p<0.01$ (for two-tailed tests, t-stats in parentheses)

Firm and quarter-year fixed effects included. Standard errors clustered by firm. The dependent variable is the change in Robinhood users in the one-hour window ending at the time indicated in the column heading. This change is scaled by average users in the window preceding the earnings announcement and then ranked into deciles, scaled to range from −0.5 to 0.5. *Intraday Abn Ret* is the cumulative abnormal return from the previous day's closing price up to the beginning of the one-hour window ending at the time indicated in the column heading. *Low AFE*, *Low SRWFE*, and *Low Intraday Abn Ret* indicate the lowest tercile of these variables. Likewise, *High AFE*, *High SRWFE*, and *High Intraday Abn Ret* indicate the highest tercile of these variables. Indicators for the middle terciles are omitted. Full variable definitions are given in Appendix A

returns and every window, except the opening window, for positive returns. Similar to Table 4, earnings surprise measures based on *SRWFE* are not significantly associated with changes in retail positions.[12] Figure 1 depicts these results, plotting the coefficients and 95% confidence intervals for the coefficients on the earnings surprise and abnormal return indicators. Overall this evidence suggests that retail investors buy into firms in response to more extreme positive and negative observed returns, consistent with more extreme returns inducing attention-driven trade.

[12] *AFE*, *SRWFE*, and *Abn. Ret.* all capture aspects of earnings news, which potentially complicates the interpretation of Table 5. However, inferences are largely unchanged when including the *AFE* or *SRWFE* measures individually or together with *Abn. Ret.* When *AFE* is included individually, the coefficient on *Low AFE* is also positive and statistically significant in the 12 pm–3 pm windows. When *SRWFE* is included individually, the coefficient on *Low SRWFE* is significantly positive in the 2 pm and 3 pm windows. *High SRWFE* becomes significantly positive in the 11 am window but insignificantly different from zero in the 3 pm window. When either the *AFE* or *SRWFE* measures are included together with the *Intraday Abn. Ret.* indicators, the results closely mirror those of Table 5.

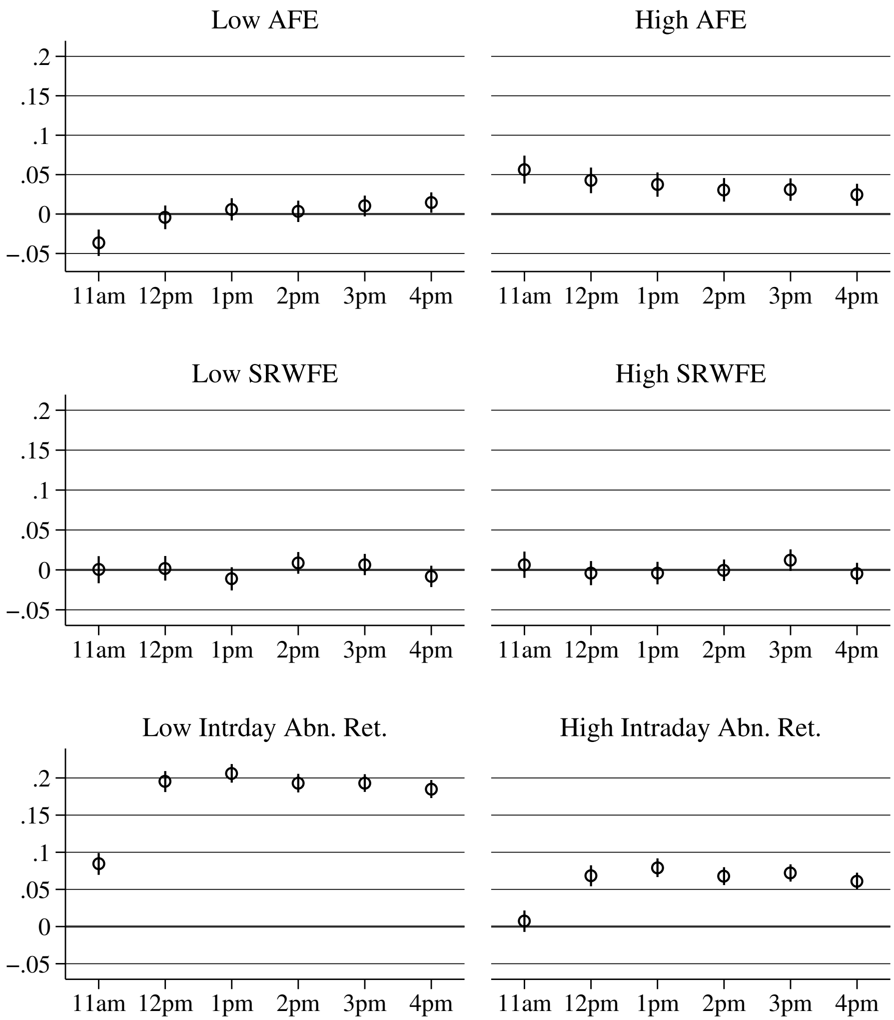

Fig. 1 Intraday Changes in Robinhood Users by Type of Earnings News. This figure plots coefficients from hourly regressions of changes in Robinhood users on the earnings announcement date on indicator variables for the lowest and highest terciles of earnings news and control variables (see Table 5). In the first set of plots, earnings news is measured using analyst forecast error (*AFE*). In the second set of plots, earnings news is measured with earnings relative to an expectation based on a seasonal random walk model (*SRWFE*). The last set of plots measures earnings news with intraday abnormal returns. Intraday abnormal returns are measured from the prior day's close to the hour preceding the plotted change in user holdings. The whiskers around each point represent 95% confidence intervals

4.4 Earnings response coefficients

I next investigate the implications of my findings so far for the pricing of earnings. The evidence presented in this section, together with that of Section 4.5, tests hypotheses H2a and H2b.

First, I examine the association between retail trades and the sensitivity of prices to earnings. To do so, I estimate the following regressions:

$$Abn.\ Ret._{i,t} = \alpha + \beta_1\ AFE + \beta_2\ \Delta\text{-}Users + \beta_3\ AFE * \Delta\text{-}Users + \beta_4\ Controls + \beta_5\ AFE^{*} Controls + \mu_i + \mu_t + \varepsilon_{i,t}. \tag{1}$$

$$\begin{aligned} Abn.\ Ret._{i,t} = {} & \alpha + \beta_1\ AFE + \beta_2\ \Delta\text{-}Users + \beta_3\ AFE^{*} \Delta\text{-}Users \\ & + \beta_4\ Low\ AFE^{*} AFE^{*} \Delta\text{-}Users + \beta_5\ High\ AFE^{*} AFE^{*} \Delta\text{-}Users \\ & + \beta_6\ Low\ AFE^{*}\ AFE + \beta_7\ High\ AFE^{*} AFE + \beta_8\ Low\ AFE^{*} \Delta\text{-}Users \\ & + \beta_9\ High\ AFE^{*} \Delta\text{-}Users + \beta_{10}\ \ Low\ AFE + \beta_{11}\ Hight\ AFE \\ & + \beta_{12}\ Controls + \beta_{13}\ AFE^{*} Controls + \mu_i + \mu_t + \varepsilon_{i,t}. \end{aligned} \tag{2}$$

Again I include firm and quarter-year fixed effects (μ_i and μ_t, respectively) and cluster standard errors by firm. As previously, the analyses use decile ranks of *Δ-Users* and *AFE*, ranging from −0.5 to 0.5. I also mean-center all control variables in these analyses to give the coefficients a more natural interpretation. The matrix of control variables includes *Size*, *MTB*, *Beta*, *Leverage*, *Persistence*, *Loss*, *Ln(Analysts)*, *Volatility*, and *Avg. Turnover*. I also interact all control variables with *AFE*.

The coefficient on *AFE* is commonly referred to as the ERC. In Eq. (1), the coefficient on the interaction term *AFE*Δ-Users* captures how the ERC varies with changes in Robinhood users during the earnings announcement. In Eq. (2), I further interact *AFE*Δ-Users* with the indicators *Low AFE* and *High AFE* to allow these associations to vary across the most negative and positive earnings surprises.

Table 6 shows the results of these analyses. Column (1) gives the results from Eq. (1). The positive and significant coefficient on the interaction *AFE*Δ-Users* shows that ERCs are more positive when there is a greater increase in Robinhood users during the earnings announcement. This result is consistent with increases in Robinhood users facilitating a more complete response to earnings (H2a) but also with an overreaction to positive earnings surprises (H2b). The results in column (2) attempt to differentiate between these alternatives. Column (2), which gives the results from estimating Eq. (2), shows positive earnings surprises drive the result in column (1). Specifically, the coefficient on *AFE*Δ-Users* in column (2), representing the effect of retail trade on the ERC when the earnings surprise is in the middle tercile, is not significantly different from zero. However, the coefficient on *High AFE*AFE*Δ-Users* is significantly positive.

These results do not clearly favor either H2a or H2b. Overall ERCs are more positive when increases in Robinhood users are greatest, consistent with H2a. But consistent with H2b, I find a more positive association between *positive* earnings surprises and returns when *Δ-Users* is greater. However, H2b also predicts a less positive association between *negative* earnings surprises and returns for greater levels of *Δ-Users*, and I find no evidence supporting this. An important caveat is that user changes and returns are measured contemporaneously in Table 6, complicating the interpretation. For example, H2b predicts more negative earnings surprises will attract Robinhood investors, and purchasing by these investors will elevate stock prices. However, the analyses of Tables 4 and 5 show Robinhood users are attracted to more extreme negative returns. Thus, while Robinhood users may contribute to

Table 6 Earnings Response Coefficient by Level of *Δ-Users*

	(1)	(2)
AFE	0.109***	0.090***
	(31.43)	(6.67)
Δ-Users	-0.044***	-0.051***
	(-15.94)	(-12.74)
*AFE*Δ-Users*	0.157***	0.048
	(15.56)	(1.07)
*Low AFE*AFE*Δ-Users*		0.076
		(1.28)
*High AFE*AFE*Δ-Users*		0.244***
		(3.68)
*Low AFE*AFE*		0.007
		(0.39)
*High AFE*AFE*		0.014
		(0.67)
*Low AFE*Δ-Users*		0.001
		(0.10)
*High AFE*Δ-Users*		-0.036**
		(-2.19)
Low AFE		-0.001
		(-0.24)
High AFE		0.005
		(1.07)
Controls	Yes	Yes
*AFE*Controls*	Yes	Yes
Adj. R-Sq	0.187	0.189
N	22,299	22,299

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ (for two-tailed tests, t-stats in parentheses)

Firm and quarter-year fixed effects included. Standard errors clustered by firm. The dependent variable is *Abn. Ret.*, the market-adjusted abnormal return on the earnings announcement date. *Δ-Users* is the difference between the number of Robinhood users holding a stock at the end of the earnings announcement date and the number of users holding a stock one day before the earnings announcement, scaled by the average number of users holding the stock during the window beginning 65 trading days before the earnings announcement and ending two trading days before the earnings announcement. *AFE* is actual quarterly EPS less the median analyst forecast of EPS, scaled by price. The analyses use decile ranks of *Δ-Users* and *AFE*, ranging from −0.5 to 0.5. *Low AFE* and *High AFE* indicate the lowest and highest terciles of *AFE*, respectively. An indicator for the middle tercile is omitted. *Controls* indicates the presence *Size*, *MTB*, *Beta*, *Leverage*, *Persistence*, *Loss*, *Ln(Analysts)*, *Volatility*, and *Avg. Turnover*. Full variable definitions are given in Appendix A

elevated prices, they are simultaneously attracted to more negative returns. The analysis of the following section alleviates this complication and helps differentiate between hypotheses H2a and H2b by examining the path of prices following the Robinhood trading that occurs at the earnings announcement.

4.5 Post-earnings-announcement drift

In my next set of analyses, I examine how firms' stock returns evolve after earnings announcements, conditional on changes in retail holdings at the earnings announcement. Hypothesis H2a predicts less drift in returns following the earnings announcement if Robinhood investors facilitate a more complete initial reaction to earnings, through either informed trading or liquidity provision. Conversely, H2b suggests greater drift in returns if attention trading by Robinhood investors distorts prices.

To investigate these possibilities, I sort firm-quarters into portfolios based on terciles of *Δ-Users* and *AFE*. Each tercile is formed independently. I then compute returns within each portfolio. First, for comparison with previous analyses, I tabulate returns on the earnings announcement date. Next I tabulate returns for the period beginning one trading day after the earnings announcement and ending 50 trading days following the earnings announcement.

Panel A of Table 7 gives these results for the full sample. The results tabulating returns at the earnings announcement mirror those from prior analyses. Earnings announcement returns are reliably negative in the most negative earnings surprise tercile (*AFE = 1)* and reliably positive in the most positive earnings surprise tercile (*AFE = 3)* across all terciles of *Δ-Users*. More interestingly, returns are more extreme in the highest tercile of *Δ-Users* (*Δ-Users* = 3) than in the lowest (*Δ-Users* = 1), as evidenced in the last row of panel A. Again the simultaneity of changes in retail positions and returns clouds interpretation. However, the results of the intraday analysis in Table 5 indicate this finding stems at least partially from Robinhood investors responding to more extreme returns. But this does not preclude the possibility that retail trading also contributes to returns.

The columns in panel A of Table 7 that correspond to returns following the earnings announcement, [EA + 1, EA + 50], show little evidence of PEAD. Cumulative abnormal returns are not significantly different from zero in either the most positive or the most negative terciles of earnings surprise (*AFE*) across all terciles of *Δ-Users*.[13] However, there is some evidence within the most positive earnings surprise tercile (*AFE* = 3) of greater positive return drift for the highest tercile of *Δ-Users*, compared with the lowest. This is inconsistent with hypothesis H2a but weakly supports H2b.

Focusing on smaller firms and those that are costly to short yields more pronounced results. Panel B of Table 7 repeats the analysis of panel A but uses only firms in the bottom tercile of *MVE*. In the window ending 50 trading days following the earnings announcement, returns for firms with the greatest increase in Robinhood users (*Δ-Users* = 3*)* exhibit positive drift following both positive and negative earnings surprises, consistent with H2b. Thus, in contrast with traditional PEAD, where returns drift in the direction of the earnings surprise (e.g., Bernard and Thomas 1989), returns for small firms drift up following both positive and negative

[13] In an untabulated test, I continue to find no evidence of PEAD in the full sample when pooling across all terciles of *Δ-Users*. Returns in both the highest and lowest *AFE* terciles continue to be insignificantly different from zero.

Table 7 Cumulative Abnormal Returns by *Δ-Users* Tercile and *AFE* Tercile

Panel A: Full Sample								
Return window:			**Earnings Announcement [EA]**			**[EA + 1, EA + 50]**		
			AFE Tercile			**AFE Tercile**		
			1	**2**	**3**	**1**	**2**	**3**
Δ-Users Tercile	1	Mean	-0.0036**	0.0223***	0.0340***	-0.2585	-1.0890***	-0.6308
		t-stat	(-2.05)	(16.19)	(17.00)	(-0.35)	(-3.41)	(-0.80)
	2	Mean	-0.0201***	0.0051***	0.0136***	1.0858	-0.4285	0.8635
		t-stat	(-15.02)	(4.02)	(7.83)	(1.27)	(-1.33)	(1.06)
	3	Mean	-0.0655***	-0.0127***	0.0444***	0.2941	-1.4885***	1.1351
		t-stat	(-19.85)	(-4.83)	(14.44)	(0.37)	(-3.99)	(1.49)
	3 – 1	Mean	-0.0619***	-0.0349***	0.0104***	0.5525	-0.3995	1.7659*
		t-stat	(-18.06)	(-11.31)	(2.87)	(0.64)	(-0.91)	(1.87)
Panel B: Small Firms (*MVE* Tercile = 1)								
Return window:			**Earnings Announcement [EA]**			**[EA + 1, EA + 50]**		
			AFE Tercile			**AFE Tercile**		
			1	**2**	**3**	**1**	**2**	**3**
Δ-Users Tercile	1	Mean	-0.0122***	0.0181***	0.0285***	1.1424	-2.4969*	2.1931
		t-stat	(-3.79)	(4.57)	(8.83)	(0.74)	(-1.80)	(1.31)
	2	Mean	-0.0257***	0.0013	0.0082***	3.0613**	-2.3491*	3.4443**
		t-stat	(-13.29)	(0.34)	(3.14)	(2.18)	(-1.76)	(2.35)
	3	Mean	-0.0570***	0.0136	0.0587***	4.2961**	-0.3816	5.8344***
		t-stat	(-9.64)	(1.11)	(10.50)	(2.36)	(-0.19)	(3.81)
	3 – 1	Mean	-0.0448***	-0.0046	0.0303***	3.1536	2.1153	3.6413*
		t-stat	(-7.10)	(-0.36)	(4.81)	(1.48)	(0.91)	(1.81)

Table 7 (continued)

Panel C: Costly to Short Firms (*Special* = 1)

Return window:			**Earnings Announcement [EA]**			**[EA + 1, EA + 50]**		
			AFE Tercile			**AFE Tercile**		
			1	**2**	**3**	**1**	**2**	**3**
Δ-Users Tercile	1	Mean	-0.0329***	0.0288	-0.0046	3.3022	-3.9851	6.6067
		t-stat	(-5.97)	(1.43)	(-0.73)	(1.11)	(-1.30)	(1.48)
	2	Mean	-0.0328***	-0.0184	-0.0066*	6.2680***	3.4564	4.5362*
		t-stat	(-10.84)	(-1.45)	(-1.83)	(2.91)	(1.47)	(1.75)
	3	Mean	-0.0366***	-0.0176	0.0222**	15.6427***	4.5503	19.8121***
		t-stat	(-3.04)	(-0.79)	(2.31)	(3.66)	(0.34)	(5.10)
	3 – 1	Mean	-0.0037	-0.0463	0.0268**	12.3405**	8.5355	13.2054**
		t-stat	(-0.28)	(-1.57)	(2.50)	(2.51)	(0.62)	(2.21)

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ (for two-tailed tests, t-stats in parentheses)

This table presents cumulative market-adjusted abnormal returns on and after earnings announcements for different terciles of *Δ-Users* and *AFE*. *Δ-Users* is the difference between the number of Robinhood users holding a stock at the end of the earnings announcement date and the number of users holding a stock one day before the earnings announcement, scaled by the average number of users holding the stock during the window beginning 65 trading days before the earnings announcement and ending two trading days before the earnings announcement. *AFE* is actual quarterly earnings per share (EPS) less the median analyst forecast of EPS, scaled by price. The [EA] window includes only the earnings announcement date. The window [EA + 1, EA + 50] begins one trading day after the earnings announcement and ends 50 trading days after the earnings announcement earnings surprises when the increase in the number of retail investors at the earnings announcement is greatest. However, the magnitude of this drift, when compared to firms with less of an increase in Robinhood investors at the earnings announcement (i.e., *Δ-Users* = 1), is significantly greater only for the most positive earnings surprises (*AFE* = 3).

Results in panel C, which focuses on firms that are costly to short, resemble those in panel B but are even more pronounced. In this analysis, I follow Beneish et al. (2015) by classifying stocks as hard to borrow, or "special," when the daily cost of borrowing score from Markit Securities is greater than two. I define the indicator variable *Special* to equal one when a firm's shares are costly to borrow and zero otherwise. Among firms that are costly to short, the upward drift in the highest tercile of *Δ-Users* is significantly more positive than in the lowest tercile for both the most negative (*AFE* = 1) and most positive (*AFE* = 3) earnings surprises. Overall Table 7 supports hypothesis H2b.

Table 7 analyzes the drift in returns following earnings announcements by examining cumulative abnormal returns at the 50th trading day following the earnings announcement. Next I take a more holistic approach and examine the entire trajectory of returns over these 50 trading days. I do this because the expected path of returns, if distorted by retail trade-induced price pressure, is unclear. If increases in retail positions push prices away from fundamentals, returns may later revert, but the timing of any reversion is uncertain. To allow for both drift and return reversals, I use a measure related to intra-period efficiency (Blankespoor et al. 2020, p. 15).

Specifically, I again sort firm-quarters into portfolios based on terciles of *Δ-Users*, *AFE*, and *MVE*. Figure 2 plots cumulative returns to date for each of these portfolios. I quantify the amount of drift in each portfolio by calculating the area between the return lines in Fig. 2 and the ending CAR on the 50th trading day following the earnings announcement. For a portfolio with a positive ending return, this is the area *above* the curve and below the horizontal line representing the CAR on day 50. I label this area the "PEAD-Area." Like Blankespoor et al. (2018), I adjust for return overreactions and reversals, although Fig. 2 shows reversals are limited in my portfolios. Unlike Blankespoor et al. (2018), I do not scale by the final cumulative abnormal return since I wish to capture both the amount and the speed of price revision following the earnings announcement. Note these areas will be larger when returns drift up or down to a greater degree and when they do so more slowly. These areas will be smaller when there is little price revision or when the price revision happens shortly after the earnings announcement.

As an example, consider Fig. 2, where the *Δ-Users* Tercile = 3 and the *MVE* Tercile = 1 (the graph in the upper right). For the most positive *AFE* tercile portfolio, the PEAD-Area roughly equals the area between the dotted line and the horizontal line where the CAR equals 6 (i.e., the area *above* the dotted line plotting the CAR). Table 8 reports that this area is equal to 149.632. Table 8 reports all the PEAD-Areas related to the portfolios shown in Fig. 2.

The results summarized in Fig. 2 are generally consistent with Table 7. The charts show a distinct upward drift in returns in the terciles where *Δ-Users* is largest and *MVE* is smallest. This upward trajectory in returns exists for the most positive and the most negative portfolios of *AFE*. To test the statistical

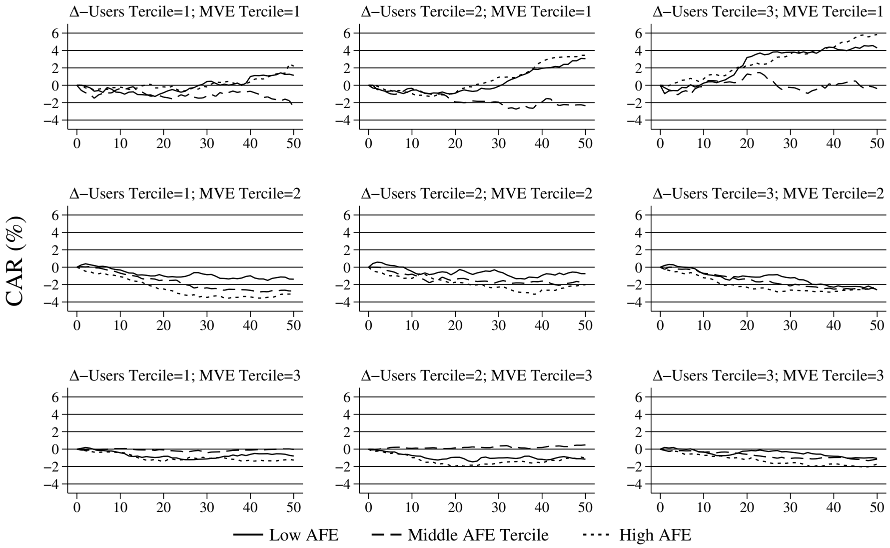

Fig. 2 CAR Over 50 Trading Days Following the Earnings Announcement by *Δ-Users* and *MVE* Tercile. This figure plots the cumulative abnormal return (CAR) for 50 trading days following the earnings announcement for portfolios of firms based on the market value of equity (*MVE*), analyst forecast error (*AFE*), and the change in Robinhood users at the earnings announcement (*Δ-Users*). Firms are sorted into portfolios based on terciles of *MVE*, *AFE*, and *Δ-Users*; each tercile is formed independently

significance of the drift in each portfolio, I take an approach conceptually similar to that of Bushman et al. (2010). This method analyzes the PEAD-Areas at the portfolio level to average away noise in the returns of individual firms. I create a null distribution for the PEAD-Area of each portfolio by randomly assigning *Δ-Users* and *MVE* tercile pairs among firms and recalculate the PEAD-Areas. I repeat this process 10,000 times to construct a distribution of PEAD-Areas under the null hypothesis that *Δ-Users* and *MVE* do not matter for the path of returns post-earnings announcement. Note that I do not randomly reassign *AFE* terciles. Rather I randomize within each *AFE* tercile. The right panel of Table 8 gives the results of testing the PEAD-Areas against the null distributions for all portfolios. In the right panel, the first number in each cell gives the difference between the PEAD-Area and the mean of the null distribution to which the portfolio relates. P-values based on the null distribution are given in parentheses.

The tests of the PEAD-Areas confirm what visual inspection of Fig. 2 makes apparent: the upward drift in the highest terciles of *Δ-Users* is significant for the smallest firms but not for the largest ones. Consistent with hypothesis H2b, this again suggests that extreme earnings surprises may prompt attention-induced purchasing among Robinhood traders, which can translate into elevated prices for smaller firms. However, while the PEAD-Areas in the highest terciles of *Δ-Users* are greater than in the lowest, these differences in the amount of drift are not statistically significant. Specifically, in the smallest *MVE* tercile and the lowest *AFE* tercile, the PEAD-Area in the highest *Δ-Users* tercile (89.268) is not significantly

Table 8 PEAD-Areas by *Δ-Users*, *MVE*, and *AFE* Terciles

		PEAD-Areas			Test of PEAD-Areas		
		Δ-Users Tercile			*Δ-Users* Tercile		
MVE Tercile:	*AFE* Tercile:	1	2	3	1	2	3
1	1	62.245	136.402	89.268	30.161	106.143	56.447
		N = 1,112	N = 1,527	N = 1,038	(0.0960)	(0.0000)	(0.0134)
	2	70.453	38.893	28.348	37.345	9.096	-4.908
		N = 156	N = 210	N = 159	(0.0440)	(0.2818)	(0.6289)
	3	103.496	140.170	149.632	51.298	89.650	98.406
		N = 832	N = 1,257	N = 1,100	(0.0699)	(0.0019)	(0.0019)
2	1	27.312	17.185	67.159	-5.397	-17.595	34.147
		N = 1,044	N = 818	N = 1,066	(0.6064)	(0.5700)	(0.0763)
	2	49.301	20.532	43.038	28.912	-2.481	21.507
		N = 773	N = 474	N = 615	(0.0071)	(0.7187)	(0.0447)
	3	43.773	30.346	29.145	-9.181	-22.879	-22.189
		N = 845	N = 766	N = 1,001	(0.6616)	(0.6355)	(0.6331)
3	1	14.302	13.846	29.479	-21.871	-23.327	-5.840
		N = 729	N = 678	N = 785	(0.6192)	(0.6053)	(0.6088)
	2	5.522	14.475	20.757	-12.964	-4.585	1.634
		N = 1,393	N = 1,117	N = 1,111	(0.0596)	(0.7683)	(0.6013)
	3	16.199	24.301	26.541	-39.358	-30.979	-29.331
		N = 519	N = 546	N = 533	(0.4557)	(0.5308)	(0.5029)

This table presents the PEAD-Areas for portfolios of firms based on the market value of equity (*MVE*), analyst forecast error (*AFE*), and the change in Robinhood users at the earnings announcement (*Δ-Users*). PEAD-Area is the area between the line plotting a portfolio's daily return and the portfolio's ending return 50 trading days following the earnings announcement (see Fig. 2). Firms are sorted into portfolios based on terciles of *MVE*, *AFE*, and *Δ-Users*; each tercile is formed independently. The left panel gives the PEAD-Area associated with each portfolio and the number of observations in the portfolio. The right panel reports the difference between the portfolio's PEAD-Area and the mean of the null distribution to which the portfolio relates; p-values are given in parentheses

greater than that in the lowest tercile (62.245). Similarly, within the smallest *MVE* tercile and the highest *AFE* tercile, the PEAD-Area in the highest *Δ-Users* tercile (149.632) is not significantly greater than that in the lowest tercile (103.496).

4.6 Post-earnings-announcement drift: short sale constraints

Finally, to provide further evidence for hypothesis H2b, I repeat the analysis of the previous section for firms whose shares are costly to borrow (i.e., costly to sell short). Shorting can facilitate price discovery and keep prices aligned with firm fundamentals (Boehmer and Wu 2013). Thus it may alleviate price pressure induced by attention-driven trade.

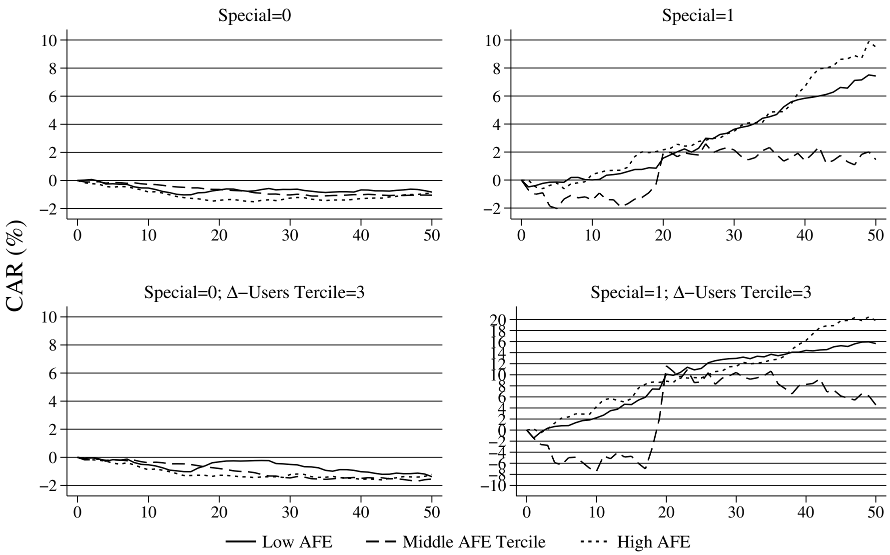

Fig. 3 Cost of Short Selling and CAR Over 50 Trading Days Following the Earnings Announcement. This figure plots the cumulative abnormal return (CAR) for 50 trading days following the earnings announcement for portfolios of firms based on the cost of short-selling (*Special*), analyst forecast error (*AFE*), and the change in Robinhood users at the earnings announcement (*Δ-Users*). The upper two graphs plot CARs by tercile of *AFE* separately for firms that are easily shorted (*Special* = 0) and firms with shares that are more costly to borrow (*Special* = 1). The lower two graphs repeat this exercise for the earnings announcements with the greatest increase in Robinhood users (*Δ-Users* = 3)

The graphs in the first row of Fig. 3 show the results when I split the sample by *Special*. The graphs show little PEAD for the more easily shorted firms (*Special* = *0*). For the firms that are costly to short, there is an upward drift in both the most positive and the most negative *AFE* terciles (p-value < 0.01; see Table 9).

The second row of Fig. 3 shows the results when restricting the sample to firms within the highest tercile of *Δ-Users*. Again there is little evidence of drift for more easily borrowed stocks. However, the upward drift following the earnings announcement is stark for stocks that are costly to borrow. Note that some of these portfolios have relatively few observations, due to independently sorting the variables. Specifically, the portfolio where *Special* equals one and *AFE* is in the middle tercile is sparsely populated. Thus the returns of this portfolio are noisy and should be interpreted with caution.

Overall the results of this analysis are consistent with H2b, showing short-selling constraints limit the ability of other investors to mitigate price pressure following increases in Robinhood users' positions at the earnings announcement. In contrast to Table 8, but similar to Table 7, the amount of drift in Table 9 in the highest *Δ-Users* terciles is significantly greater than that in the lowest terciles. Specifically, untabulated results show that, when *Special* equals one, the PEAD-Area within both the highest and lowest terciles of *AFE* is significantly greater in the highest *Δ-Users* tercile than in the lowest *Δ-Users* tercile (p-vales of 0.06 and < 0.00, respectively).

Table 9 PEAD-Areas by Specialness

		PEAD-Areas		Test of PEAD-Areas	
		Special		*Special*	
	AFE Tercile:	0	1	0	1
Full Sample	1	10.319	225.338	-16.029	194.002
		N = 7,492	N = 1,300	(0.0000)	(0.0000)
	2	16.689	64.367	0.750	19.557
		N = 5,932	N = 76	(0.4913)	(0.2287)
	3	19.196	302.155	-30.505	250.275
		N = 6,394	N = 1,002	(0.0000)	(0.0000)
Highest *Δ-User* Tercile	1	35.829	314.636	8.185	264.444
		N = 2,601	N = 286	(0.3489)	(0.0000)
	2	28.334	294.091	10.486	207.182
		N = 1,867	N = 18	(0.0940)	(0.0045)
	3	14.887	476.309	-35.036	414.205
		N = 2,338	N = 295	(0.0163)	(0.0000)

This table presents the PEAD-Areas for portfolios of firms based on the cost of short-selling (*Special*), analyst forecast error (*AFE*), and the change in Robinhood users at the earnings announcement (*Δ-Users*). The PEAD-Area is the area between the line plotting a portfolio's daily return and the portfolio's ending return 50 trading days following the earnings announcement (see Fig. 3). *Special* takes a value of one if a firm's stock is costly to borrow and zero otherwise. Firms are also sorted into terciles of *AFE* and *Δ-Users*. The left panel gives the PEAD-Area associated with each portfolio and the number of observations in the portfolio. The top three rows include all observations; the bottom three rows are based on only the highest terciles of *Δ-Users*. The right panel reports the difference between a portfolio's PEAD-Area and the mean of the null distribution to which the portfolio relates; p-values are given in parentheses

5 Conclusion

Reduced trading costs and more accessible trading venues are encouraging more retail investors to trade actively in capital markets. This paper documents the association between this growing prevalence of retail trading and the pricing of earnings. To do so, I use data on retail investors' holdings from the Robinhood trading platform. I test how earnings surprises and stock returns predict changes in the number of Robinhood users holding a firm's stock during its earnings announcement. I analyze positive and negative earnings news separately, as well as intraday trading and returns, to better understand whether these investors respond to earnings news or the visibility the earnings announcement provides. Finally, I examine retail trading and stock returns in the weeks that follow the earnings announcement.

The literature documents conflicting results on the capital market effects of retail trading. Some work finds evidence of sentiment or attention-driven trading, which contributes to price pressure, driving prices away from fundamental value. Other work finds evidence that retail traders can contribute to efficient markets through liquidity provision and informed trading. This literature notes that the mixed results likely stem from heterogeneity among retail investors, thus highlighting the importance of refined samples. While results from my sample of Robinhood investors likely will not generalize to other populations of retail investors or other time windows, my results speak to the behavior of the type of investor underlying the current retail trader boom and the effects of their trading on the market's pricing of financial performance.

Findings indicate that the retail traders in my sample exhibit behavior that is most consistent with attention-driven trade. First, changes in the positions of these investors pre earnings announcement do not positively predict earnings news. Second, Robinhood investors buy in response to both positive and negative earnings news. This result is most consistent when earnings news is measured using abnormal returns at the earnings announcement, although investor holdings are also associated with earnings surprises measured relative to analyst expectations. Finally, intraday analysis suggests that Robinhood investors respond to returns following the release of earnings news, instead of the earnings release itself. Overall these patterns are most consistent with attention-induced trade.

My results also show how activity by Robinhood traders is associated with returns at and following the earnings announcement. The market response to earnings surprises is more pronounced when these investors increase their holdings of a firm's shares during the earnings announcement. Announcements with positive earnings news drive this result. Following the earnings announcement, more extreme earnings surprises, both positive and negative, are associated with an upward drift in future returns for smaller firms and firms that are costly to short. This upward drift in returns suggests Robinhood investors contribute to price pressure when market frictions exist. Future work may help us better understand whether and when the upward return drift I document reverts and whether this reflects a transfer of wealth away from retail investors. Future work might also illuminate whether these apparent price distortions influence firm decisions and capital allocation.

Whether low-cost, frictionless access to financial markets through apps such as Robinhood benefits or harms retail investors remains an open question. Research suggests active trading by individuals is deleterious to their wealth (Barber and Odean 2000). However, much of the underperformance associated with active trading can be attributed to transaction costs. Explicit transaction costs have shrunk in recent periods, as most retail-oriented brokerages have eliminated trading commissions. Still, retail traders incur implicit trading costs, such as the bid-ask spread, and commission-free brokerages, such as Robinhood, potentially contribute to wider spreads. These brokerages can offer commission-free trades because they generate revenue by selling retail orders to wholesalers (i.e., payment for order flow). Ostensibly, retail investors benefit from this model, as they avoid trading commissions and receive an execution price as least as good as the current market quotation. They may receive price improvement, relative to quoted prices, if the broker shares the payment for the order received from the wholesaler. But payment for order flow can exacerbate transaction costs related to bid-ask spreads by routing retail order flow away from exchanges. Brokerages strategically routing uninformed order flow away from exchanges will increase adverse selection concerns on exchanges, resulting in higher spreads (Battalio and Loughran 2008). These concerns have led the SEC to propose rules aimed at limiting the practice of routing retail orders to wholesalers (SEC 2022).

More broadly, the prevalence of first-time investors using Robinhood suggests that Robinhood and similar platforms encourage individuals to invest in the stock market. And stock market participation is reliably associated with greater wealth (e.g., Bertaut and Starr-McCluer 2000; Calvet et al. 2007). Thus, even if an individual's initial trades lose money, the longer-term effects of equity ownership on wealth may be positive. New investors may graduate from chasing meme stocks to less speculative strategies. Robinhood's mission states that "everyone should have access to the financial markets," and Robinhood appears to attract a demographic of investor that is less likely to use traditional brokerages. In congressional testimony, Robinhood's CEO stated: "African American investors represented nine percent of Robinhood's customer base, compared with just three percent at incumbent firms … Hispanic investors accounted for 16 percent of Robinhood's customers, compared with seven percent at incumbent firms" (Testimony of Vladimir Tenev, 2021, p. 4). Potentially, Robinhood benefits its customers by introducing them to the stock market. Conversely, a negative early investing experience could discourage some investors from continuing to invest, as research shows past experiences can have lasting effects on risk-taking and investment (Malmendier and Nagel 2011). Discerning the social impact of Robinhood and related services is beyond the scope of this paper, and I leave it to future work to investigate the effects of fintech innovations on stock market participation, individual wealth, and wealth inequality.

Appendix A: Variable Definitions

Abn. Ret.............	The market-adjusted abnormal return on the earnings announcement date.
Low Abn. Ret......	An indicator variable taking a value of one if an observation is in the lowest (i.e., most negative) tercile of *Abn. Ret.* and zero otherwise.
High Abn. Ret.....	An indicator variable taking a value of one if an observation is in the highest (i.e., most positive) tercile of *Abn. Ret.* and zero otherwise.
Δ-Users.............	The difference between the number of Robinhood users holding a stock at the end of the earnings announcement date and the number of users holding the stock one day before the earnings announcement, scaled by the average number of users holding the stock during the window beginning 65 trading days before the earnings announcement and ending two trading days before the earnings announcement. The analyses use decile ranks of this variable, ranging from −0.5 to 0.5 (i.e., decile ranks from 0 to 1 and then subtract 0.5 so the hypothetical median takes a value of zero).
Δ-Users, Prior...	The difference between the number of Robinhood users holding a stock two trading days before the earnings announcement date and the number of users holding the stock 65 trading days before the earnings announcement date, scaled by the average number of users holding the stock during this window.
AFE..................	Actual quarterly earnings per share (EPS) less the median analyst forecast of EPS, scaled by price.
Low AFE..........	An indicator variable taking a value of one if an observation is in the lowest (i.e., most negative) tercile of *AFE* and zero otherwise.

High AFE.........	An indicator variable taking a value of one if an observation is in the highest (i.e., most positive) tercile of *AFE* and zero otherwise.
SRWFE............	Actual quarterly EPS less actual EPS from the same fiscal quarter one year prior, scaled by price.
Low SRWFE.....	An indicator variable taking a value of one if an observation is in the lowest (i.e., most negative) tercile of *SRWFE* and zero otherwise.
High SRWFE....	An indicator variable taking a value of one if an observation is in the highest (i.e., most positive) tercile of *SRWFE* and zero otherwise.
Size.................	Logarithm of market value of equity.
MTB................	Market value of equity divided by book value of equity.
Persistence......	The coefficient of EPS regressed on lagged EPS within firm, using up to 10 years of data.
Ln(Analysts).....	Logarithm of the number of analysts contributing to the median forecast on which *AFE* is based.
Volatility..........	The standard deviation of daily returns over the period beginning 65 trading days before the earnings announcement and ending two days before the earnings announcement.
Avg. Turnover...	Average daily volume divided by shares outstanding during the period beginning 65 trading days before the earnings announcement and ending two days before the earnings announcement.
Beta................	The coefficient from regressing daily firm return less the risk-free rate on market returns less the risk-free rate over the 252 trading days ending three trading days before the earnings announcement.
Leverage..........	Total debt divided by the book value of equity.
Loss................	An indicator variable taking a value of one if EPS is negative and zero otherwise.
Special...........	An indicator variable taking a value of one if a firm's stock is costly to borrow and zero otherwise (Beneish et al. 2015).

Acknowledgements I thank seminar participants at the Four School Accounting Research Conference at NYU, Northwestern University, The Ohio State University, Purdue University, University of Illinois Chicago, University of Iowa, University of Minnesota, the Wharton School, and the 2022 Hawaii Accounting Research Conference, as well as Elizabeth Blankespoor (editor), Brian Bushee, James Celia, Ed deHaan, Cristi Gleason, Vicki Wei Tang (discussant), Andrew Van Buskirk, Tzachi Zach, Frank Zhang (discussant), and an anonymous reviewer for their helpful comments. I also thank Frankie Shi for research assistance.

Declarations

Competing Interests The author has no competing interests.

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