How Do Brokerages' Digital Engagement Practices Affect Retail Investor Information Processing and Trading? *

Austin Moss♠
Henry B. Tippie College of Business
University of Iowa

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Abstract

I investigate how retail brokerages' digital engagement practices (e.g., push notifications and simplified information presentation) impact retail investor information processing and trading. My identification strategy exploits a unique institutional feature of Robinhood in which it automatically sends push notifications to its customers when the intraday return of a stock in their portfolio reaches +/- 5%. Using an intraday event study design, I document that push notifications significantly increase retail investor trading by at least 25% in the fifteen minutes following notifications. I then exploit this discontinuous increase in the proportion of investors trading on Robinhood with similar information sets to examine whether the salient display of accounting information induces retail investors to incorporate the information in their trades. By reconstructing the earnings information displayed on Robinhood, I find that accounting information saliency increases the use of earnings surprise information by retail investors. Notably, Robinhood displays earnings information in a way that an investor's visual perception of earnings news displayed on Robinhood differs from how accounting academics have typically transformed it into a value-relevant information signal (i.e., scaling unexpected earnings by stock price). When I examine whether retail investors use the academic earnings surprise in their investment decisions, I consistently find that they do not. Lastly, I show that the aggregate influence of these digital engagement practices has a small, positive impact on retail investor informativeness.

Keywords: Retail Investors, Digital Engagement Practices, Information Processing, Accounting Information

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♠ Email: austin-moss@uiowa.edu. Website: austinmoss.me. Postal address: Henry B. Tippie College of Business, W252 Pappajohn Business Building, Iowa City, Iowa 52242.

"[Digital engagement practices (DEPs)] may encourage investors to trade more often, invest in different products, or change their investment strategy. Predictive analytics and other DEPs often are designed with an optimization function to increase revenues, data collection, or customer time spent on the platform. This may lead to conflicts between the platform and investors…I'm particularly focused on how we protect investors engaging with technologies that use DEPs."

– Gary Gensler, SEC Chair, August 27th, 2021

1. Introduction

In May 2021, over 16 million retail investors in the United States accessed their brokerage account through a mobile app—an increase of over 1,600% compared to January 2017 (Statista, 2021). Facilitating a significant portion of the increase in mobile trading are new entrants to the retail brokerage market, such as Robinhood®, Webull®, and Public.com®, who have focused on providing a mobile-first trading environment. For example, Robinhood operated for three years and amassed over two million users before it allowed customers to trade through a web interface, and Public.com is following a similar strategy, amassing over one million users without providing a web-based trading platform. An important contributor to these brokerages' success is their significant use of digital engagement practices, which the U.S. Securities and Exchange Commission (i.e., SEC) describes as "… *design elements or features designed to engage with retail investors on digital platforms.*" Digital engagement practices have recently come under intense scrutiny by the SEC because of the potential for brokerages to use these tools to influence investor behavior. In this paper, I examine whether digital engagement practices affect investor information processing and trading by focusing on three notable digital engagement practices: (i) push notifications, (ii) information saliency, and (iii) information display.

Whether digital engagement practices provide net benefits or costs to retail investors is unclear. On one hand, digital engagement practices can exacerbate the known biases and mistakes that retail investors exhibit. For instance, push notifications that include information about recent price movements might exacerbate attention-driven trade or return chasing biases (e.g., Greenwood and Nagel, 2009). In fact, the state of Massachusetts filed a complaint against Robinhood for its "*use of strategies such as gamification to encourage and entice continuous and repetitive use of its trading application*" (Massachusetts Securities Division, 2020). On the other hand, digital engagement practices can significantly reduce investor information processing costs. Continuing the example above, investors can automate their investment monitoring activities by relying on push notifications to inform them about important firm events, significantly decreasing information awareness costs and increasing the speed in which they can react to market information. Understanding the welfare effects of digital engagement practices is further complicated by the fact that each type of engagement practice is likely to affect investors differently.

I exploit several features of the Robinhood trading app to investigate the effect that digital engagement practices have on retail traders' behavior and their acquisition and use of information. First, Robinhood customers automatically receive push notifications when the price of a stock they own (or have on their watchlist) moves five percent higher or lower intraday (Figure 1).[1] I use this feature to identify when Robinhood customers receive push notifications and then examine the effect of push notifications on retail investor trading activity. Second,

[1] Robinhood also sends push notifications when stock prices move ten percent intraday. I focus on the sample of five percent notifications because they are significantly more common and the pre-event period is not confounded by an earlier notification (i.e., five percent notifications are sent out prior to ten percent notifications).

Robinhood provides a limited amount of firm information through their trading platform, increasing the saliency of the information they choose to make available (Figure 6). Using a set of variables that reconstruct the information set available in the Robinhood app, I test whether information saliency affects the incorporation of earnings information into investors' trading decisions. Third, Robinhood displays a firm's earnings information as a scatterplot with the range of the Y-axis being a function of the minimum and maximum earnings values over the last four quarters (Figure 7). Relative to how accounting academics measure the magnitude of earnings surprises (i.e., scaling unexpected earnings by share price), the visual display of earnings information can distort the perceived magnitude of the earnings news. I use this unique source of variation resulting from how investors perceive information to investigate whether the specific manner in which information is displayed on mobile apps impacts retail investor trading independent from the underlying information itself. Lastly, I examine the combined effect of these digital engagement practices on retail investor informativeness.

My identification strategy exploits the precise timing of when Robinhood sends notifications to its customers. Using an intraday, staggered-adoption event study design, I analyze retail investor behavior using fifteen-minute event windows around the dissemination of push notifications, which I identify as occurring when a stock's intraday return crosses the +/-5% threshold.[2] I examine the positive and negative return samples separately and measure retail investor activity following the method developed in Boehmer, Jones, Zhang, and Zhang (2021).[3]

[2] Only stock-days that reach an intraday return greater than or equal to five percent in absolute magnitude are retained in my sample.

[3] I do not use the Robintrack dataset introduced by Moss, Naughton, and Wang (2020) because it captures ownership activity and not trading activity. I discuss the pros and cons of using the Boehmer et al. (2021) measure to capture Robinhood-specific trading in more detail in Section 3.2.

With the inclusion of stock-day fixed effects, this design uses retail investor behavior during the windows immediately before push notifications as the counterfactual behavior that would occur in the post-event windows absent a Robinhood notification. The pre-period behavior is a reasonable counterfactual for several reasons. First, prices generally take a couple hours to reach the notification-triggering threshold of +/- 5%, creating temporal distance between the push notifications and the underlying event that causes the price movement. Second, my analyses utilize short event windows of only fifteen-minutes, meaning that some unobserved factor would need to occur systematically during the fifteen-minute window following push notifications to drive my results. Lastly, the information available to investors does not change dramatically in the 60 minutes surrounding Robinhood notifications. For these reasons, I interpret the large, discrete changes that occur following the dissemination of push notifications as an effect of the notification.

While the discrete jumps in retail investor activity are large enough that they cannot be explained by pre-trends, the pre-trends still confound my estimates of effect size. Therefore, to correct for the pre-trend, I adjust my event study estimates using the two-stage least squares proxy variable approach developed in Freyaldenhoven, Hansen, and Shapiro (2019). To facilitate a causal interpretation in an event study design with pre-trends in the outcome variable, this methodology requires a proxy variable that is affected by the unobserved confound (i.e., price-moving event) but not affected by the event of interest (i.e., Robinhood push notification).[4] In

[4] A pre-trend in unadjusted retail investor activity is expected since investors can be reacting to the price-moving event or the level of returns prior to five percent. For instance, intraday price movements of four percent are relatively uncommon, garnering retail investor attention, and it would not be surprising if there was increased retail trading on these days. Importantly, these are relatively smooth changes in investor activity around the five percent notification threshold.

my setting, I identify non-retail investor trading as a proxy variable that meets these criteria. Non-retail investors respond to price-moving events and the subsequent price movements but are unlikely to be impacted by push notifications from Robinhood. Intuitively, this approach adjusts the event study estimates of retail investor trading for the (scaled) event study estimates of non-retail investor trading. Relative to alternative design choices, such as estimating a difference-in-differences model or including the proxy directly in the event study model as a control variable, this methodology requires less stringent assumptions about how the unobserved confound affects the outcome of interest (Freyaldenhoven et al., 2019; Freyaldenhoven, Hansen, Perez, and Shapiro, 2021).

I first investigate how push notifications informing investors of a five percent price movement impacts the intensity and direction of retail trading. Push notifications likely influence investor trading through two primary channels. First, push notifications are attention-grabbing events that are likely to increase retail trading intensity (Arnold, Pelster, and Subrahmanyam, 2021). The ‘attention’ effect of a push notification refers to the act of bringing the stock to the front of an investor’s mind (e.g., the effect of a hypothetical push notification that simply displayed the stock symbol without the additional price movement information). The attention channel should not have a direct impact on the direction of trade in this setting because the investors who receive notifications are almost all owners (Barber and Odean, 2008). However, since attention induces more trade, it likely exacerbates pre-existing investor mistakes and biases. Second, push notifications inform investors of significant stock price changes. The ‘information processing’ effect of a push notification refers to the act of making an investor aware of a piece of information. The awareness of a large price movement is likely to induce retail trading since the new price represents either a better buying or selling opportunity, depending on the investor's investment thesis and the direction of the stock price move.

For both the positive and negative return samples, I find an increase in the number of retail trades following push notifications. The number of retail trades in the fifteen minutes following notifications is 28% higher than the fifteen minutes preceding the notification, and over the one hour following a notification event, I estimate that 1% of Robinhood customers who own the notification stock engage in a trade. When I examine buy and sell trades separately, the results across the positive and negative samples differ dramatically. Following a positive five percent notification, retail investor selling activity accounts for 75% of the increase in total trades.[5] In contrast, buying activity accounts for 83% of the increase in trades following negative notifications.[6] Additionally, coefficient estimates from placebo event studies around an intraday return of four percent are either statistically insignificant from zero, economically and statistically smaller than the corresponding push notification estimates, or of the opposite sign.[7] Taken together, these results show that push notifications exert a strong influence on retail investor behavior and that the direction of this influence is dependent on whether the push notification is triggered by positive or negative returns.

Next, I investigate the importance of information saliency in nudging retail investors to use certain information signals by examining whether the salient display of earnings information results in investors using it to trade. Information saliency might benefit retail investors by

[5] In the fifteen minutes after a positive push notification, there are eight additional retail trades and six of these trades are sales.

[6] In the fifteen minutes after a negative push notification, there are six additional retail trades and five of these trades are purchases.

[7] The results from the placebo event studies are untabulated in this draft but available upon request. I plan to incorporate the results into future revisions.

nudging them to process important, value-relevant information, which they might otherwise neglect or underweight in their investment decision. This benefit is particularly true for inexperienced retail investors who might not know which signals are value-relevant nor how to acquire them, so they default to information that is readily available. Furthermore, a necessary condition for information saliency to benefit investors is for the information to be value-relevant. If irrelevant signals are made salient, then retail investors could attend to these signals at the expense of processing more valuable signals, hurting the performance of their trades (Elliott, Gale, and Hobson, 2021). In my setting, a sizeable literature demonstrates that earnings information is a value-relevant information signal (e.g., Kothari, 2001).

A challenge in identifying the information used by retail investors in their trading decisions is the disperse and unobservable nature of their information set. However, I overcome this impediment by leveraging my previous results, which show that a sizeable proportion of retail investors who are trading after push notifications do so through Robinhood. As a result, I can identify the information set of a significant portion of retail traders. That is, push notifications concentrate investor attention on the information available in the Robinhood app. To test the importance of information saliency, I reconstruct the Robinhood information set available to investors on the push notification date and compare the association between earnings surprise and retail order imbalance in the pre and post periods.

I find evidence consistent with information saliency being an influential digital engagement practice that nudges retail investors to incorporate earnings information into their trades. Using a measure of earnings surprise based on its visual display in Robinhood, I find that a one standard deviation increase in earnings surprise moderates the net selling reaction to positive push notifications by about 4%. This effect size is economically meaningful as it is approximately 50% as large as a one standard deviation increase in the past year's returns. For negative push notifications, a one standard deviation increase in earnings surprise moderates the net buying reaction by 6%, an effect size similar in magnitude to a one standard deviation increase in the past year's returns. Oddly, the results from the negative return sample suggest that retail investors use earnings surprise information by trading in the opposite direction of earnings surprise. One possible explanation for this behavior is that negative notifications evoke strong emotions and, to delay the realization of being wrong, investors ignore information contrary to their original purchase decision (e.g., Barberis and Xiong, 2012). Overall, the results from this analysis indicate that information saliency is an influential tool that can be used to help retail investors incorporate value-relevant signals into their trading decisions.

Building on the saliency results showing that retail investors use earnings surprise information in their trades, I examine whether retail investors use information as it is displayed or if they acquire and use the underlying information signal. The way that earnings information is displayed by Robinhood induces variation between an investor's visual perception of a firm's earnings surprise and how accounting academics typically transform it into a value-relevant information signal. When I repeat the information saliency tests using unexpected earnings scaled by stock price, I consistently find that retail investors *do not* use this information in their trading decisions. This is true with and without the other information variables in the regression as well as with and without the inclusion of the visual earnings surprise measure. These results indicate that how brokerages display information impacts investors' information acquisition and integration activities.

My final set of analyses examine the aggregate influence of digital engagement practices on the informativeness of retail investors who are induced to trade after push notifications. To assess the aggregate influence of digital engagement practices on the informativeness of retail investors, I test whether retail order imbalance better predicts the cross-section of one-week ahead returns before or after push notifications. I find that positive push notifications lead to more informed trading in the post-notification period. A one standard deviation increase in post-notification retail order imbalance predicts one-week ahead market-adjusted returns that are 0.05 percentage points larger than the same increase in the pre-notification period. However, when examining the negative push notification sample, I do not find a significant change in retail informativeness after a push notification. Together, these results suggest there might be a small, positive effect on retail informativeness, particularly following positive push notifications.

My paper contributes to several streams of literature. First, in contrast to the conclusion in Blankespoor, deHaan, Wertz, and Zhu (2019) that individual investors disregard earnings information, I find that retail investors use earnings information when digital engagement practices provide earnings news in an easily accessible fashion. There are several differences between our studies that could lead to the contrasting results. One likely explanation is that my setting looks at retail investors who have already shown interest in the company—either through owning the stock or placing the stock on their watchlist—and have some prior knowledge about the company. For these investors, earnings surprise information might be more valuable or easier to incorporate into their trading decisions because they have a better understanding of how or why reported earnings deviated from expectations. A simpler explanation, however, is that retail investors simply do not use "unexpected earnings scaled by stock price" as an information signal. Rather, they use some other transformation of unexpected earnings.

I also contribute to a growing literature that studies the use of mobile technologies by financial market participants. Using data on individuals trading CFDs in the United Kingdom, Arnold et al. (2021) document that push notifications, which they call “attention-triggers”, increase investor risk-taking. Grant (2020) and Elliott et al. (2021) study the influence of mobile devices and information push, respectively, on investor judgments in experimental labs. Elliott et al. (2021) find that pushing only value-relevant information to investors increases the processing of the pushed information and the accuracy of value estimates. Grant (2020) finds that mobile devices harm investor judgments. My results, however, show that aspects of the mobile trading environment can be leveraged to nudge investors into using more value-relevant information signals.

Over the last two years there has been a significant increase in research studying Robinhood investors. Moss, Naughton, and Wang (2020) introduce a dataset tracking the trading activities of Robinhood investors and study whether these investors make portfolio reallocation decisions based on environmental, social, and governance (i.e., ESG) disclosures. Barber, Huang, Odean, and Schwarz (2021) examine attention-induced herding events, showing that Robinhood investors are more likely than other retail investors to herd and that Robinhood’s “Top Mover List” plays a key role in coordinating these herding events. Lastly, Michels (2021) examines how Robinhood investors trade around earnings announcements, showing that Robinhood investors seem to respond to the price movements caused by earnings announcements but not the underlying earnings information.

My paper is also relevant to current regulatory discussions. SEC Chairman Gary Gensler mentioned in several speeches throughout 2021 that the SEC is interested in better understanding the impact of digital engagement practices on retail investing and whether regulation is required to protect investors. While much of the discussion in the media has focused on the “gamification” aspect of digital engagement practices, much less attention has been paid to the potential benefits of digital engagement practices. My study suggests potential benefits to digital engagement practices that decrease investors' information processing costs (Blankespoor et al., 2019; Blankespoor, deHaan, and Marinovic, 2020). I document two engagement practices that have the potential to lower information processing costs. First, push notifications reduce information awareness costs, as this task is automated for significant events. Second, information saliency decreases information acquisition and integration costs by nudging investors to use value-relevant information. On the flipside, however, if information saliency and display nudge investors to use value-relevant information signals then these same tactics can influence investors to use value-irrelevant signals.

2. Institutional Features

2.1 Robinhood Trading Platform

Founded in 2014, Robinhood is a relative newcomer to the retail brokerage market. The brokerage was the first to popularize zero-commission trading, which the rest of the brokerage industry quickly adopted, and the company was built around mobile-enabled trading. In fact, from 2015 to 2018 Robinhood users could only make trades through the mobile app. Likely a result of being focused on mobile trading, Robinhood is known for its simple user interface and engaging design features. Recently, regulators criticized some of these features for "gamifying" stock trading, yet Robinhood says that many of their features benefit investors and help build trust between investors, Robinhood, and the stock market (Robinhood Markets, 2021).

These design features have seemingly paid-off for Robinhood as it is one of the most popular retail brokerages. As of June 30, 2021, Robinhood had over 21 million monthly active users. Robinhood investors are also highly engaged with the app and their investments. On any given day, customers visiting the Robinhood app do so an average of seven times (Robinhood Markets, 2021). Furthermore, Robinhood investors "*traded nine times as many shares as E-Trade customers, and 40 times as many shares as Charles Schwab customers, per dollar in the average customer account*" during the first quarter of 2020 (Popper, 2020). Robinhood's use of push notifications and a simplistic user interface are two notable reasons that customers are so highly engaged with their investments, and I study whether these features are harmful to retail investors, as suggested by the media and regulators, or beneficial to retail investors, as claimed by Robinhood.

2.2 Robinhood Push Notifications

One digital engagement practice that Robinhood employs is the use of push notifications (Figure 1). These notifications are not new features to mobile phones and are a common tool for mobile apps of any kind to alert the user of important updates. While your email app updates you that you have a new email, the Robinhood app updates you about events occurring in your investment account. These updates include events such as trades being filled, dividend or interest payments being deposited, upcoming earnings announcements, and significant intraday price movements.

I study the push notifications specifically about intraday price movements for several reasons. First, these notifications are determined by a stock-level attribute (i.e., the stock's price movement relative to the most recent closing price). This feature is important because I do not have access to individual account data that would be required to identify notifications specific to an individual. Second, Robinhood price movement notifications are set to occur at the same thresholds for all users. This feature allows me to identify the precise timing of when push notifications are sent. Furthermore, the same price trigger for all users increases my ability to detect an effect, if it exists, because a large quantity of market participants receive the notifications at the same time, concentrating their reactions into a relatively small timeframe. If investors customize the price thresholds at which they receive notifications, then the impact of notifications is spread across different levels of price movements and is likely unidentifiable.[8] Lastly, the Robinhood app defaults into users receiving these notifications. This ensures that the majority of Robinhood investors who own the stock will receive the notifications when they are triggered.

2.3 Robinhood's Simplified User Interface

Besides pioneering zero-commission trades, Robinhood is perhaps best known for its simplified user interface. While a simple, easy to use interface lowers the barriers to trading, successfully increasing market participation by millions of investors who are far more diverse than traditional investors, it might also lead to excessive or uninformed trading (Barber et al., 2021). As Barber et al. (2021) point out, *"[The] streamlined and simplified interface likely guides the choices of Robinhood users.*"

Robinhood makes a relatively small amount of firm information available to investors. In addition to basic summary statistics such as market capitalization, volume, and dividend yield, Robinhood provides a historical returns chart, a few media headlines, a summary of analyst recommendations, and a chart of the last four quarters of actual and expected EPS (Figure 6). Limiting the amount of information easily accessible to investors might hurt trading performance

[8] Other trading apps such as TD Ameritrade, Fidelity, and Vanguard allow investors to set price alerts on a stock-by-stock basis and at any price they choose.

if investors should incorporate information that is omitted. However, if limiting the information available to investors signals that the information displayed is value-relevant and important to incorporate into trading decisions, then a simplified information environment could benefit retail traders. Signaling to investors which information is value-relevant is likely to be particularly beneficial to investors new to the stock market—a demographic that makes up over 50% of Robinhood users (Lam, 2021).

I focus on the increased salience of earnings information because this information is known to be value-relevant (e.g., Kothari, 2001) and recent studies find that retail investors neglect earnings information when making trading decisions (e.g., Blankespoor et al., 2019, Michels, 2021). In a setting where there are many investors using the same, observable information set, I study whether the simplified information environment on the Robinhood platform "guides" or "nudges" retail investors to use earnings news in trading decisions.

3. Data

3.1 Identifying Robinhood Push Notifications and Sample Selection

My sample consists of stock-days for which I identify that Robinhood sent a push notification about the stock on that trading day. Since Robinhood notifications are triggered by intraday price movements of +/- 5%, I use these return thresholds to identify the timing of push notifications. Specifically, for each five-minute interval during every stock-trading day from 2017-2020, I use New York Stock Exchange Trades and Quotes (TAQ) data to calculate whether any trade occurred at a price at least five percent higher or lower than the previous closing price. I designate the first five-minute interval to reach the +/- 5% threshold as the push notification event window. Since retail trades are relatively sparse at the five-minute frequency, I aggregate the five-minute intervals into fifteen-minute intervals for my analyses, beginning with the five-minute intervals immediately before and after the five-minute event window. Further, for the purposes of labeling event windows in relative time, I designate the first fifteen-minute window after a Robinhood push notification as t=0. For example, if Apple reaches an intraday return of 5% at 11:03am then t=0 occurs from 11:05-11:20am and t+1 from 11:20-11:35am, while t-1 occurs from 10:45-11:00am and t-2 from 10:30-10:45am. I continue to create event-time windows in this fashion during normal market hours. I drop the five-minute window in which the push notification occurred and windows that do not span a full fifteen minutes due to market hours (e.g., a window spanning 9:30-9:40am or 3:55-4:00pm).

My sample construction starts with all security-days available on TAQ that I identify as triggering a push notification between January 1, 2017 and December 31, 2020. I eliminate securities that do not merge to CRSP or Compustat or that are not common U.S. equities. I drop firms in the treated arms of the SEC's Tick Size Pilot because the experiment changed a stock's minimum tick size, which interferes with the methodology that I use to measure retail investor trading (Boehmer et al., 2021). For this same reason, I exclude stock-days with any trade at a price less than $1. Additionally, not all securities are available on Robinhood to trade, particularly early in my sample. Using the Robintrack dataset, which tracks the number of Robinhood users who own each stock, I eliminate stocks from my sample that were never available to trade on Robinhood during the time that Robintrack collected data from May 2018 to August 2020. Lastly, I drop any stock-day with less than two event windows before and after the push notification so that my analyses using a single post indicator variable use a balanced panel of data. This restriction eliminates notifications within 30 minutes of market open and market close. Together, these restrictions result in positive and negative five percent push notification samples including 136,894 and 142,256 stock-days, respectively.

3.2 Measuring Retail Investor Trades

I measure retail trading using the methodology developed in Boehmer et al. (2021).[9] Using institutional details about how retail and institutional trades get filled in the U.S. stock market, Boehmer et al. devise a clever method to identify retail trades as well as whether these trades are buy trades or sell trades. Specifically, most retail trades are routed to wholesalers, such as Citadel Securities, who fill the orders. Since regulations require that retail investors receive the best available price, the wholesalers often fill the order with sub-penny price improvement compared to the standing best bid or ask price, which exchanges require to be quoted at one-cent increments. Retail trades are then identified from TAQ as coming from a FINRA trade reporting facility (TAQ exchange code "D") with fractional penny prices between $0.00 and $0.004 as well as $0.006 and $0.01, not inclusive of $0.00 and $0.01. Trades in the $0.00-$0.004 range are considered buys, while trades in the $0.006-$0.01 range are considered sells.

Although the method from Boehmer et al. (2021) captures retail trading from many brokerages—not just Robinhood, there are a few reasons why this measurement error should not significantly affect the inferences of my study. First, my inferences are based on institutional features that are specific to the Robinhood trading platform. I checked multiple popular trading platforms and none had push notification settings that defaulted to a 5% intraday price trigger.

[9] I do not use Robintrack data because it captures stock ownership rather than trading activity. In my setting, most of the investors who receive the notifications already own the stock so no purchase activity would be captured and only selling all of one's position would be captured. Not only would this bias effect sizes towards zero, but since no buying activity is captured and some selling activity is captured it may also bias estimates towards push notifications causing relatively more selling activity.

Second, I examine changes in retail investor behavior during a small window around the Robinhood push notifications. Third, the Boehmer et al. (2021) measure of retail trades captures non-directed marketable orders. According to Robinhood's recent SEC Rule 606 filing, over 90% of Robinhood orders are of this type. In contrast, Boehmer et al. (2021) state their measure likely captures around 50% of trades from other major brokerages such as Fidelity, TD Ameritrade, E-Trade, etc.

However, it is likely that using the Boehmer et al. (2021) measure *understates* the effect of Robinhood push notifications when expressed as a percentage of pre-period retail trading. Perfect measurement of the effect of Robinhood notifications expressed as a percentage change would be calculated as the change in the number of Robinhood trades scaled by the base number of Robinhood trades in the pre-period. For the reasons discussed in the previous paragraph, the numerator of this calculation using the Boehmer et al. (2021) measure (i.e., the change in retail investor trades from pre-notification to post-notification) is mostly driven by Robinhood investors. However, the denominator of this calculation (i.e., number of retail trades in the pre-period) includes Robinhood trades as well as trades from investors using other retail brokerages. Relative to a perfect measure of Robinhood trading, the measurement error inflates the denominator of the calculation, decreasing the overall percentage change. Unfortunately, I have no way of estimating how understated my effect sizes are, and thus, I simply point out this aspect of my study for readers to keep in mind.

4. Research Design and Results

4.1 Robinhood Push Notifications and Retail Investor Trading

My first analysis examines how push notifications impact the intensity and direction of retail investor trading using an intraday event study design. The basic event study model underlying my research design is:

$$\textit{Retail Reaction}_{i,t} = \sum \beta_t \textit{Event Window}_{i,t} + \textit{Fixed Effects} + \varepsilon_{i,t} \qquad (1)$$

Retail Reaction is either *Retail Trades*, *Retail Buys, Retail Sells,* or *Retail Order Imbalance*. *Retail Trades* is defined as the total number of retail investor trades in fifteen-minute event window *t*. *Retail Buys* and *Retail Sells* are defined analogously for retail buy trades and sell trades, respectively. *Retail Order Imbalance* captures net retail buys and sells and is defined as the number of retail buy trades less the number of retail sell trades scaled by the total number of retail trades. I multiply *Retail Order Imbalance* by 100 for easier interpretation of coefficients. Descriptive statistics for all four measures of retail investor reaction are presented in Table 1.

Event Window is a vector of eighteen indicator variables ranging from *t-9+* to *t+8+*, where t=0 is the first fifteen-minute window after a Robinhood push notification. The *Event Window* indicator variables are equal to one if the fifteen-minute window is *t* windows from the push notification window. I combine all event windows more than eight windows away from the push notification into two bins—one for pre-event windows and one for post-event windows. Further, I exclude the *Event Window(t-1)* indicator variable to normalize its coefficient to zero, facilitating interpretation of the other coefficients, and to allow for identification of the fixed effects (Freyaldenhoven et al., 2021). *Fixed Effects* includes *Stock-Day Fixed Effects* to isolate the identifying variation to differences in retail trading activity before and after a stock-day's push notification. I also include *Time of Day Fixed Effects* to control for intraday seasonality in retail investor activity and the timing of push notifications (Farrell, Green, Jame, and Markov, 2021).

The results of estimating Equation 1 are presented in Figure 2. In almost all the event study plots, there is a significant change in *Retail Reaction* that occurs immediately after the push notifications. Looking at *Retail Reaction* in the pre-notification windows, however, shows that *Retail Reaction* begins drifting around *Event Window(t-4)* in the same direction as the post-notification jump. Unfortunately, this pre-trend in *Retail Reaction* will confound any estimate of the impact of push notifications. Therefore, I do not interpret these results until the effect estimates are adjusted for the pre-trend in the data.

To adjust for the pre-trends and collect a more accurate estimate of effect size, I use the two-stage least squares proxy variable approach developed in Freyaldenhoven et al. (2019). This methodology flexibly controls for unobserved confounding (i.e., price-moving events) using a proxy variable that is affected by the unobserved confounding but not affected by the treatment of interest (i.e., push notifications). I use non-retail trades as the proxy variable in my setting as price-moving events impact non-retail traders but push notifications likely do not. To implement this methodology, I estimate the following equations using two-stage least squares:

First Stage: $\textit{Non-Retail Trades}_{i,t} = \sum \gamma_t \textit{Event Window}_{i,t} + \textit{Fixed Effects} + \varepsilon_{i,t}$ (2)

Second Stage: $\textit{Retail Reaction}_{i,t} = \sum \beta_t \textit{Event Window}_{i,t} + \gamma \textit{Fitted Non-Retail Trades}_{i,t}$

$$+ \textit{Fixed Effects} + \varepsilon_{i,t} \quad (3)$$

In the first stage equation (Equation 2), I instrument *Non-Retail Trades*, defined as the total number of non-retail investor trades, using the *Event Window(t-1)* indicator variable as an excluded instrument and the remaining variables defined in Equation 1 as included instruments. The second stage equation (Equation 3) includes *Fitted Non-Retail Trades*, the predicted value from the first stage equation, as a control variable and excludes the *Event Window(t-1)* indicator variable. Further, since an *Event Window* indicator still needs to be dropped to allow for identification of the fixed effects, Equation 3 also excludes the *Event Window(t-2)* indicator variable.

The intuition underlying how the two-stage approach works is best explained graphically. Figure 3 presents an event study plot with the proxy variable, *Non-Retail Trades*, as the dependent variable. Notice the similar patterns between this figure and the coefficient plots in Figure 2, with *Retail Reaction* as the dependent variable. Since *Non-Retail Trades* is not impacted by Robinhood push notifications, I use its post-event dynamics to adjust *Retail Reaction* for its change absent the notifications. To visualize this adjustment, the unadjusted event study estimates for *Retail Reaction* are overlayed with the scaled event study estimates for *Non-Retail Trades* in Figure 4. The coefficient estimates for *Non-Retail Trades* are scaled such that the *Event Window(t-2)* coefficient is equal to the *Event Window(t-2)* coefficient for *Retail Reaction*. This figure visually demonstrates the similarity in pre-trends. Further, the adjustment that the two-stage least squares approach makes is easy to visualize as well. The approach subtracts the scaled *Non-Retail Trades* coefficients from the unadjusted *Retail Reaction* coefficients to calculate the adjusted coefficient estimates for *Retail Reaction*, shown in Figure 5.

The pre-trends across all measures of *Retail Activity* for both positive and negative push notification samples are flat in the adjusted event study plots shown in Figure 5 and there remains a sizeable change in retail investor activity after the push notification. The results for the positive return sample are presented in Panel A. In the fifteen minutes after a Robinhood push notification the total number of retail trades increases by about eight trades. Compared to the 29 retail trades in the fifteen minutes before a notification, retail trading increases by 28%. Looking at buy and sell trades separately shows that the increase in total retail investor trading is driven by an increase in sell trades. The relatively larger increase in sell trades is confirmed by the retail order imbalance plot. Retail order imbalance drops from 6% net buys at t-1 to approximately -10% immediately after a notification. Interestingly, all the measures of retail trading activity revert to their pre-notification level within about sixty minutes.

Panel B presents the adjusted event study estimates for the negative return sample. Across all four measures of retail investor reaction, there is not a meaningful trend in the pre-period. Total retail trades increase by six immediately after push notifications. This reaction is slightly smaller than the reaction to positive notifications. Unlike positive notifications, the increase in total trades is driven by an increase in buy trades. Specifically, retail buy trades increase by five, while retail sell trades increase by one. Retail order imbalance shows the same pattern of a relative increase in buys than sells.

Overall, my results demonstrate that push notifications are a particularly effective digital engagement practice. Push notifications have a significant impact on the amount of retail investor trading, increasing the number of retail trades by at least 28% in the minutes following a notification. Further, notifications induce net selling behavior after positive push notifications and net buying behavior after negative push notifications.

4.2 Earnings Information Display and Retail Investor Use

My next analysis examines whether retail investors use the salient display of earnings information. Relative to other brokerage platforms, Robinhood uses data visualizations to display relatively little firm information on a simple, easily accessible interface. These design choices make earnings information more salient on the Robinhood platform. Figure 6 provides examples of the Robinhood and TD Ameritrade mobile apps. The earnings information is arguably more salient in the Robinhood app, with less overall information and earnings information displayed visually using a chart. To test whether the salient display of earnings information induces retail investors to incorporate the information in their trading decisions, I estimate the following model using ordinary least squares (i.e., OLS) regression:

$$\textit{Retail Order Imbalance}_{i,t} = \beta\, \textit{Post2}_{i,t} * \textit{Std. RH Earnings Surprise}_{i} + \sum \gamma_k\, \textit{Post2}_{i,t} * \textit{Std. RH Info Set}_{i} + \gamma\, \textit{Post2}_{i,t} + \textit{Fixed Effects} + \varepsilon_{i,t} \quad (4)$$

Retail Order Imbalance is either *Retail Order Imbalance*, as defined in Section 4.1, or *Adjusted Retail Order Imbalance,* which is a measure of retail order imbalance adjusted using the two-stage least squares approach from Section 4.1. Specifically, when estimating Equations 2 and 3 with *Retail Order Imbalance* as the dependent variable in the second stage equation, I calculate *Adjusted Retail Order Imbalance* as *Retail Order Imbalance - γFitted Non-Retail Trades* where γ is the estimated coefficient from Equation 3.[10]

[10] Since *Adjusted Retail Order Imbalance* is a 'generated regressor' and is thus an estimate itself, regressions including this variable should have the standard errors adjusted, typically using a bootstrap method (Chen, Hribar, and Melessa, 2020). However, due to computational limitations, I have not implemented this adjustment yet. I am currently working on a solution.

Post2 is an indicator variable equal to one for the two event windows immediately after a push notification and equal to zero for the two event windows immediately prior to a push notification. All other event windows are dropped from the analysis. *RH Earnings Surprise* is a proxy for how retail investors visually perceive the previous quarter's earnings surprise on the Robinhood app. I provide an example of an earnings chart displayed on Robinhood in Figure 7. Specifically, the Robinhood app displays actual and expected earnings information using a scatterplot where the Y-axis values are adjusted so the chart fits all the actual and expected earnings values over the previous four quarters. Thus, the maximum value on the Y-axis is determined by the maximum actual or expected EPS value from the prior four quarters, and the minimum value on the Y-axis is determined in the same way but for the minimum EPS value. I refer to the distance between the maximum Y-axis value and the minimum Y-axis value as the "height" of the Robinhood earnings chart. To construct *RH Earnings Surprise*, I scale unexpected earnings by the "height" of the Robinhood earnings chart. To facilitate interpretations of effect sizes across the information variables available to Robinhood investors, I standardize *RH Earnings Surprise* and the variables represented by *RH Info Set* to have a mean equal to zero and standard deviation equal to one.

RH Info Set represents control variables for the other information signals that Robinhood displays on its platform. These variables include $Return_{t-5,t-1}$, $Return_{t-63,t-1}$, and $Return_{t-253,t-1}$ representing returns over the last week, three months, and one year, respectively, as well as *Analyst Buy %* and *Analyst Sell %*, which are defined as the percentage of analysts with a buy or sell recommendation, respectively. The other major information source that Robinhood provides are recent media headlines. Unlike historical returns, analyst recommendations, and earnings information, I am unable to recreate a variable measuring the headlines available through

Robinhood because only three out of many possible articles are shown. Further, the information in recent article headlines is likely captured by the past week's stock returns (i.e., $Return_{t-5,t-1}$). *Fixed Effects* continues to include *Stock-Day Fixed Effects* and *Time of Day Fixed Effects*.

The results from estimating different specifications of Equation 4 are presented in Table 2. The results in Panel A are estimated on the positive five percent push notification sample. In all four columns, I examine whether the association between a stock's most recent earnings surprise and retail order imbalance is greater in the post-notification period than pre-notification period. Across all four columns, the coefficient estimate for *Post2*Std. RH Earnings Surprise* is positive and significant, indicating that retail investors use earnings surprise information to trade after Robinhood push notifications. Based on the coefficient estimate of 0.34 in Column 2, a one standard deviation increase in *RH Earnings Surprise* moderates the net selling after a positive push notification by 3.9%. On its own, this seems like it might be a relatively small effect. However, compared to the coefficient estimates on the other information variables available through Robinhood, the effect is economically meaningful. The effect of *RH Earnings Surprise* is about 53% as large as the effect of $Return_{t-253,t-1}$.

The results in Panel B are estimated on the negative five percent sample. Across all four columns, the coefficient of interest, *Post2*Std. RH Earnings Surprise*, is negative and significant. While this result suggests that retail investors incorporate earnings surprise information into their trades when it is more salient, they do so in a way that is opposite of expectations. However, comparing the coefficients across Panel A and B, the signs of several other information variables also flip such as *Post2*Std.* $Return_{t-63,t-1}$ and *Post2*Std.* $Return_{t-253,t-1}$. One possibility that might explain the flipped signs is that receiving a negative five percent push notification evokes a more behavioral response than positive notifications, resulting in less informed trade. For example, a retail investor might only use information that reinforces their past decision to purchase the stock. Overall, the results from Table 2 indicate that information saliency is an influential tool that can be used to help retail investors incorporate value-relevant signals into their trading decisions.

In the previous results, I use a measure of earnings surprise constructed to mimic how Robinhood investors are likely to perceive the earnings information as displayed by Robinhood. However, this measure of earnings surprise is not how the academic accounting literature has typically transformed earnings surprise into an informative, value-relevant signal (i.e., by scaling unexpected earnings by stock price). Therefore, I use the variation between earnings surprise as displayed by Robinhood (i.e., *RH Earnings Surprise*) and earnings surprise as measured by accounting academics (i.e., *Academic Earnings Surprise*) to examine whether the specific manner in which information is displayed on mobile apps impacts retail investor trading independent from the underlying information signal.

In Table 3, I present results from estimating Equation 4 using *Academic Earnings Surprise* instead of *RH Earnings Surprise*. In the positive five percent sample shown in Panel A, the coefficient estimate for *Post2*Std. Academic Earnings Surprise* is statistically insignificant in all four columns, indicating that retail investors *do not* use earnings surprises—as measured by accounting academics—in their trading decisions. This result is in sharp contrast to the findings in Panel A of Table 2 where the results indicate a significant use of *RH Earnings Surprise* by retail investors. Looking at the negative five percent sample in Panel B, the coefficients of interest are negative and marginally statistically significant. Lastly, in Table 4, I estimate Equation 4 using both measures of earnings surprise. The inferences from examining both surprise measures at the same time are largely similar to the inferences from examining them separate. One potentially different inference is that in the negative return sample the effect of *Academic Earnings Surprise* is no longer statistically significant. Overall, the results from Tables 2-4 indicate that the specific manner in which brokerages display information impacts investors' information acquisition and integration activities.

4.3 Robinhood's Digital Engagement Practices and Retail Investor Informativeness

My last analysis examines the aggregate influence of the digital engagement practices that retail investors interact with following a Robinhood push notification on the informativeness of retail trading. I measure retail informativeness as the association between retail order imbalance and market-adjusted returns over the next week. Specifically, to compare retail informativeness in the post push notification period to the pre push notification period, I estimate the following equation using OLS regression:

$$\begin{aligned} \textit{Market-adjusted Return}_i = \beta\, \textit{Post2}_{i,t} * \textit{Retail Order Imbalance}_{i,t} + \gamma\, \textit{Post2}_{i,t} \\ + \gamma\, \textit{Retail Order Imbalance}_{i,t} + \textstyle\sum \gamma_k\, \textit{Controls} + \textit{Fixed Effects} + \varepsilon_{i,t} \end{aligned} \tag{5}$$

Market-adjusted Return is the stock's return over the next five trading days (t+1,t+5) less the return on the value-weighted market index over the same five days. *Post2* is as defined previously. *Retail Order Imbalance* is either *Retail Order Imbalance* or *Adjusted Retail Order Imbalance* as defined in Section 4.2. I standardize *Retail Order Imbalance* and *Adjusted Retail Order Imbalance* to facilitate interpretation of the results. *Controls* include *lnMVE*, the natural logarithm of the stock's market value of equity, and *lnMB*, the natural logarithm of one plus the market to book ratio after it has been winsorized to be between 0 and 100, as well as $Return_{t-5,t-1}$, $Return_{t-63,t-1}$, and $Return_{t-253,t-1}$, which are as defined previously. Since *Market-adjusted Return* does not vary intraday, I cannot use *Stock-Day Fixed Effects* in this model. Therefore, I use *Year-*

Month Fixed Effects and *Time of Day Fixed Effects*. In some specifications, I allow the coefficients on the main effects of *Retail Order Imbalance* and *Controls* to vary each month but do not report the coefficients for brevity.[11]

The results from estimating Equation 5 are presented in Table 5. Looking at the positive return sample results in Panel A, the association between both measures of retail order imbalance and market-adjusted returns over the next five trading days increases after Robinhood push notifications. The coefficient estimate in Column 2 indicates that a one standard deviation increase in retail order imbalance predicts future returns that are 0.07 percentage points greater after a notification than a similar increase in retail order imbalance before a notification. However, the overall statistical significance of these estimates is weak and should be interpreted with caution.

The retail informativeness results estimated on the negative return sample are displayed in Panel B. The coefficient estimates across all four columns are statistically insignificant and small in magnitude. This result indicates that retail trading after push notifications is not more informed than retail trading prior to push notifications. However, the result also suggests that retail investors are not *less informed* after a push notification. Although I do not test this directly, I speculate that the 'flipped sign results' from my tests analyzing the use of information by retail investors are related to the lack of a positive effect on retail informativeness.

[11] I allow control variable estimates to vary on a monthly-basis in an attempt to control for residual variation in the dependent variable, decreasing the standard errors on my coefficient of interest.

5. Conclusion

In this paper, I examine whether digital engagement practices affect investor information processing and trading by focusing on three notable digital engagement practices: (i) push notifications, (ii) information saliency, and (iii) information display. To investigate these digital engagement practices, I exploit several institutional features of the Robinhood trading app. First, I identify when Robinhood sends its customers push notifications about large price movements. Using a two-stage least squares approach to estimating event study models with pre-trends in the outcome variable (Freyaldenhoven et al., 2019), I show that push notifications have a significant impact on retail investor trading. Next, I examine whether the salient display of earnings information induces retail investors to use it in their trade decisions. Using an earnings surprise measure intended to capture the visual perception of earnings information displayed in the Robinhood app, I find that retail investors use earnings surprise information in their trading decisions. However, I do not find any evidence of retail investors using earnings surprise information when earnings surprise is measured following the academic accounting literature. These results suggest that retail investors use earnings surprise information as it is displayed to them but do not acquire information on the underlying information signal. Lastly, I find that the aggregate influence of these digital engagement practices has a small, positive impact on retail investor informativeness.

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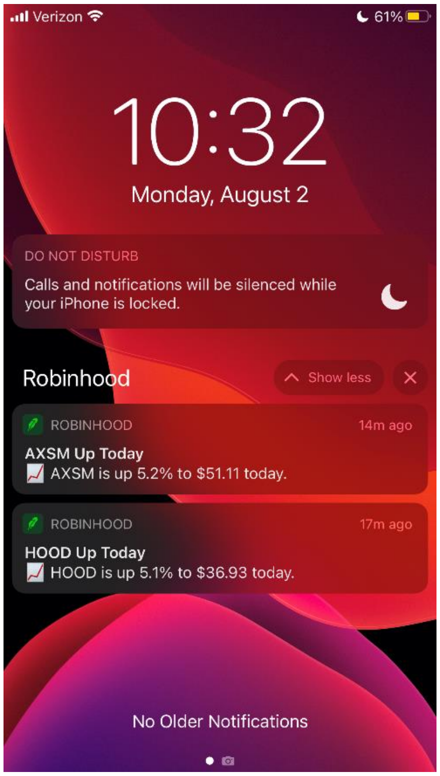
Figure 1: Example of Robinhood Push Notification

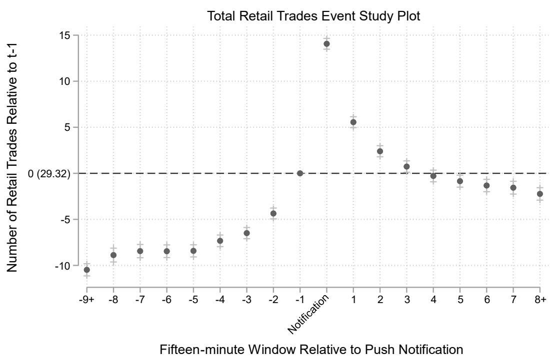


This figure shows an example of Robinhood's mobile push notifications.

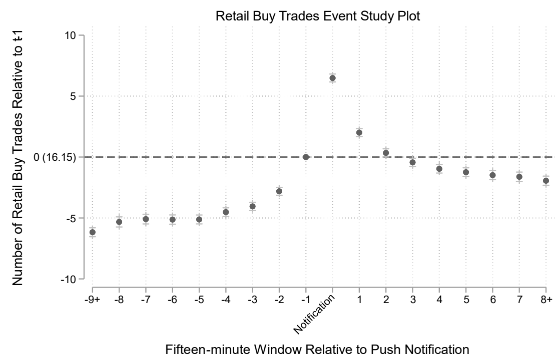
Figure 2: *Retail Reaction* Event Study Plots

Panel A: Positive 5% Push Notification Sample

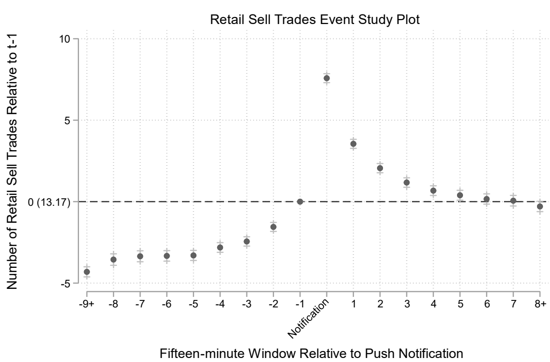
Total Retail Trades



Retail Buy Trades



Retail Sell Trades



Retail Order Imbalance

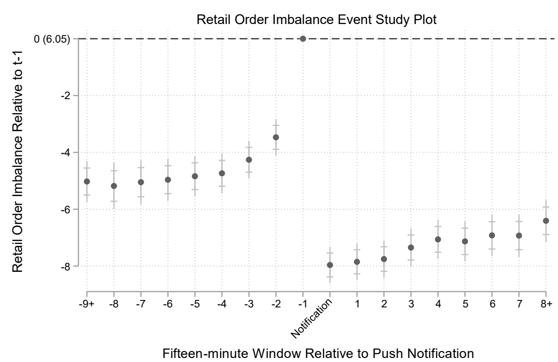


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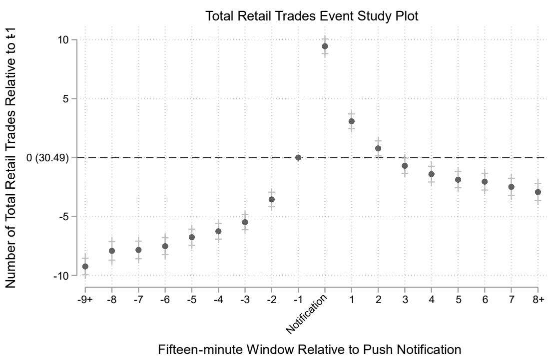
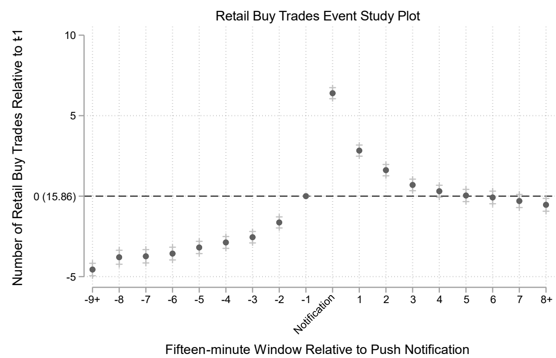
Figure 2: *Retail Reaction* Event Study Plots

Panel B: Negative 5% Push Notification Sample

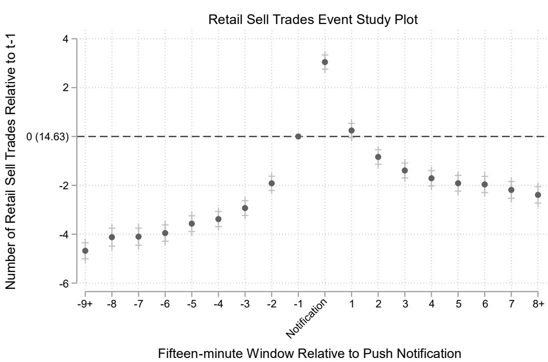
Total Retail Trades



Retail Buy Trades



Retail Sell Trades



Retail Order Imbalance

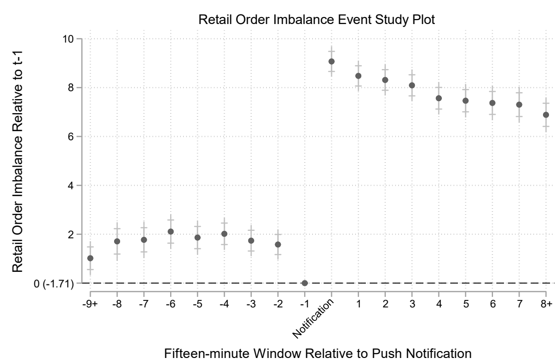
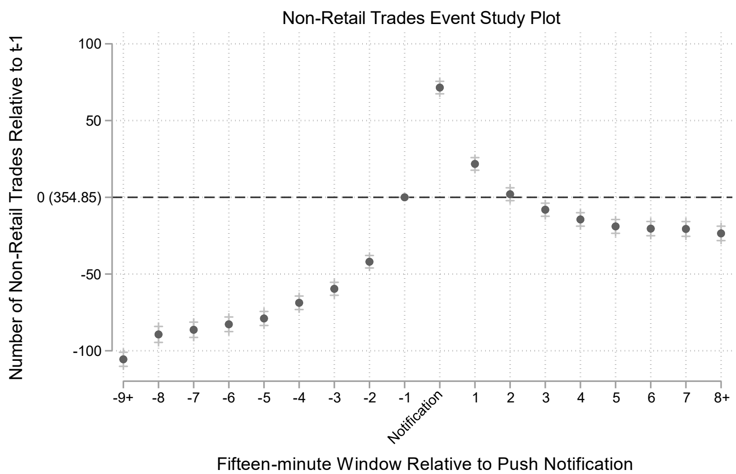


Figure 2 shows event study plots from estimating Equation 1. Panel A shows estimates from the positive five percent sample, and Panel B shows estimates from the negative five percent sample. The dependent variable is indicated above each plot. The event window t=0 (labeled "Notification" in the plots) is the first fifteen-minute window after a Robinhood push notification. The coefficient estimate at t-1 is normalized to equal zero. The coefficient estimates on the remaining event windows measure the level of *Retail Reaction* (dependent variable) relative to the level at t-1. To facilitate interpretation of the magnitude of coefficient estimates, I have included the average level of *Retail Reaction* during the t-1 window next to the 'zero' reference line on the Y-axis.

Figure 3: *Non-Retail Trade* Event Study Plots

Panel A: Positive 5% Push Notifications Sample

Total Non-Retail Trades



Panel B: Negative 5% Push Notifications Sample

Total Non-Retail Trades

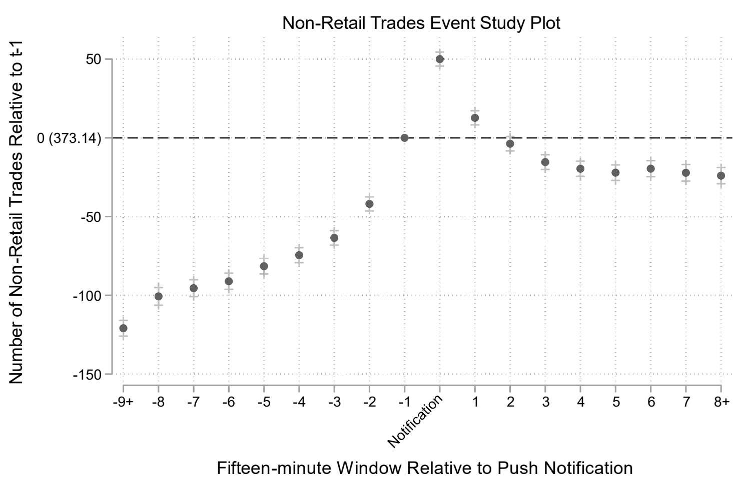
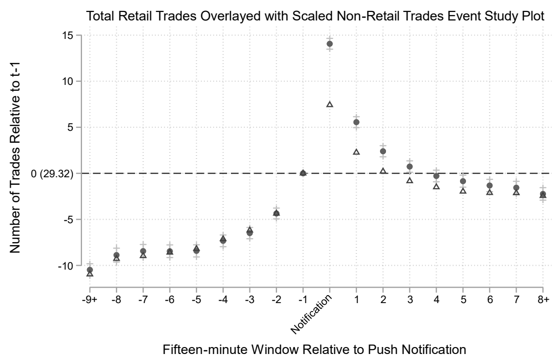


Figure 3 shows event study plots from estimating Equation 1 using *Non-Retail Trades* as the dependent variable. The event window t=0 (labeled "Notification" in the plots) is the first fifteen-minute window after a Robinhood push notification. The coefficient estimate at t-1 is normalized to equal zero. The coefficient estimates on the remaining event windows measure the number of non-retail trades relative to the number of trades at t-1. To facilitate interpretation of the magnitude of coefficient estimates, I have included the average number of non-retail trades during the t-1 window next to the 'zero' reference line on the Y-axis.

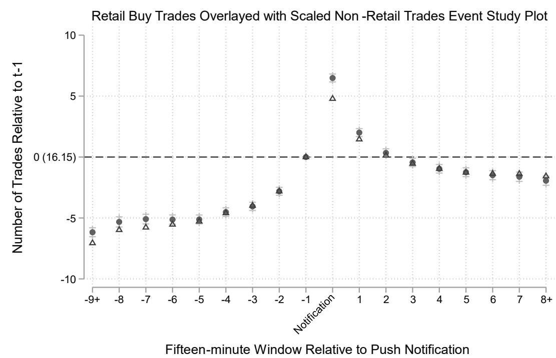
Figure 4: *Retail Reaction* Plots Overlayed with Scaled *Non-Retail Trades* Plots

Panel A: Positive 5% Push Notifications Sample

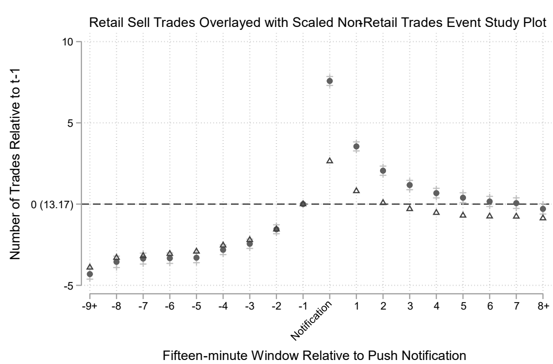
Total Retail Trades



Retail Buy Trades



Retail Sell Trades



Retail Order Imbalance

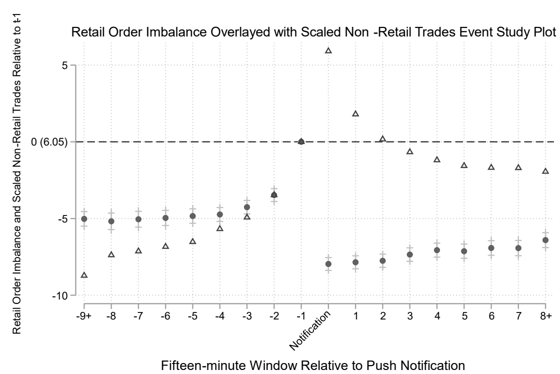


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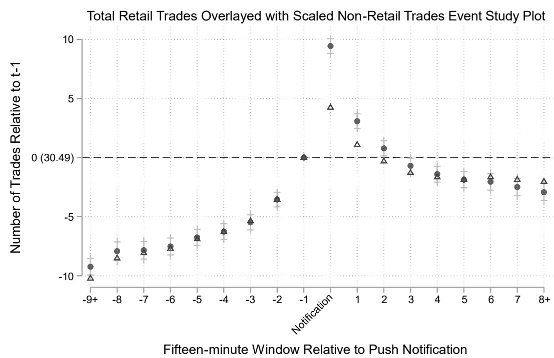
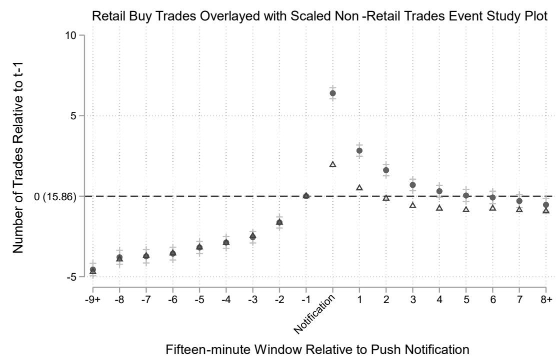
Figure 4: *Retail Reaction* Plots Overlayed with Scaled *Non-Retail Trades* Plots

Panel B: Negative 5% Push Notification Sample

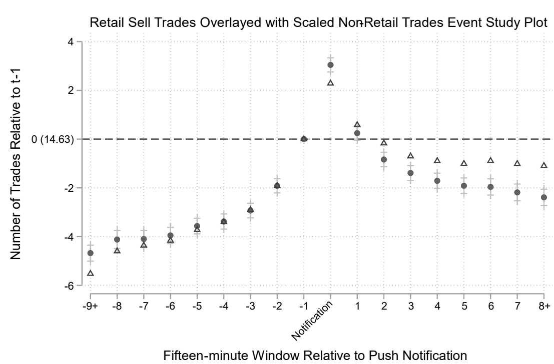
Total Retail Trades



Retail Buy Trades



Retail Sell Trades



Retail Order Imbalance

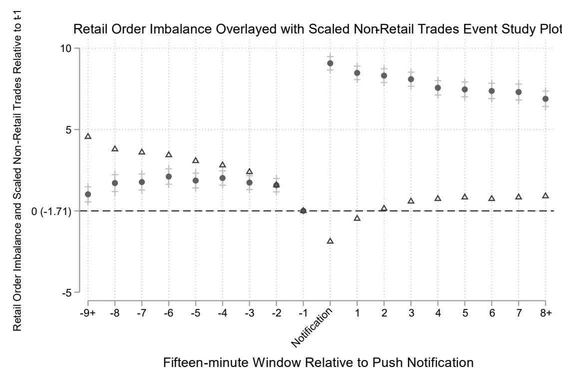
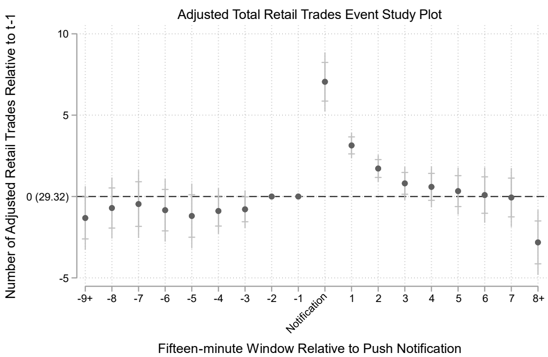


Figure 4 shows the event study plots from Figure 2 (i.e., *Retail Reaction* event study plots) as the dots with error bars overlayed with the scaled event study plots from Figure 3 (i.e., *Non-Retail Trades* event study plots) as the triangles. Panel A shows estimates from the positive five percent sample, and Panel B shows estimates from the negative five percent sample. The dependent variable is indicated above each plot. The event window t=0 (labeled "Notification" in the plots) is the first fifteen-minute window after a Robinhood push notification. The coefficient estimate at t-1 is normalized to equal zero. The *Non-Retail Trades* coefficient estimates are scaled such that the coefficient at t-2 is equal to the coefficient at t-2 for the *Retail Reaction* estimate. The coefficient estimates on the remaining event windows measure the level of *Retail Reaction* (circles with error bars) or *Non-Retail Trades* (empty triangles) relative to the level at t-1. To facilitate interpretation of the magnitude of coefficient estimates, I have included the average level of *Retail Reaction* during the t-1 window next to the 'zero' reference line on the Y-axis.

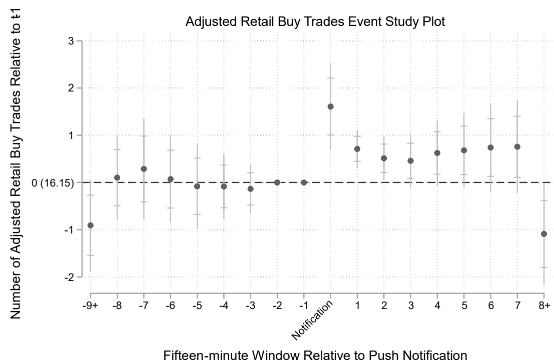
Figure 5: Adjusted *Retail Reaction* Event Study Plots

Panel A: Positive 5% Push Notification Sample

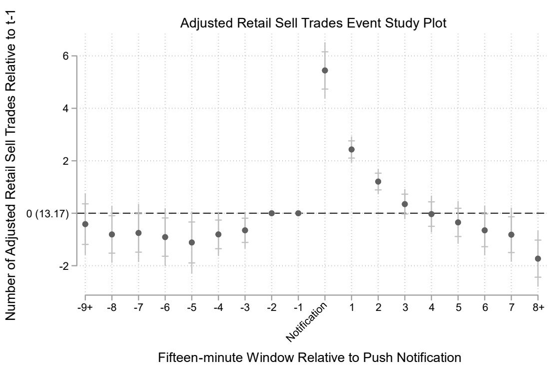
Total Retail Trades



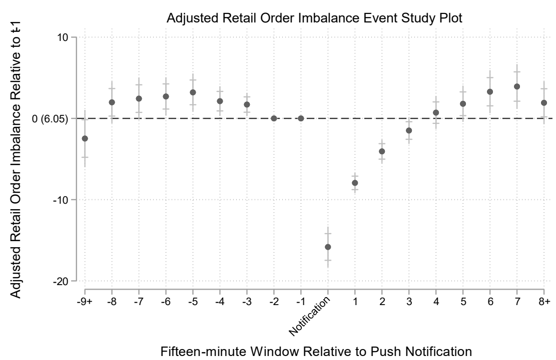
Retail Buy Trades



Retail Sell Trades



Retail Order Imbalance

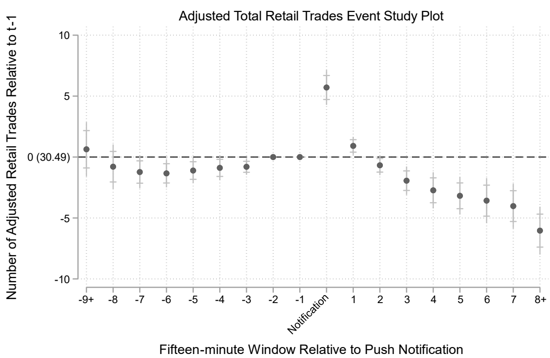


(Continued)

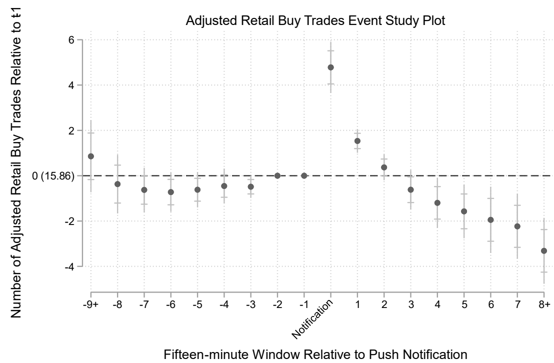
Figure 5: Adjusted *Retail Reaction* Event Study Plots

Panel B: Negative 5% Push Notification Sample

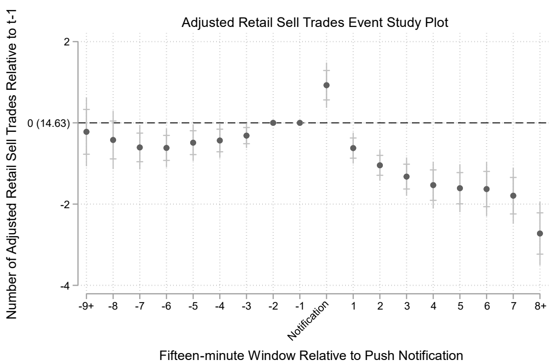
Total Retail Trades



Retail Buy Trades



Retail Sell Trades



Retail Order Imbalance

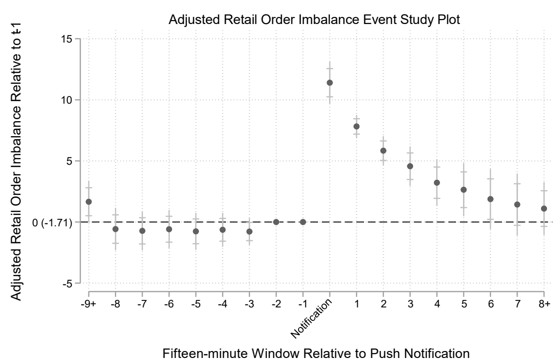
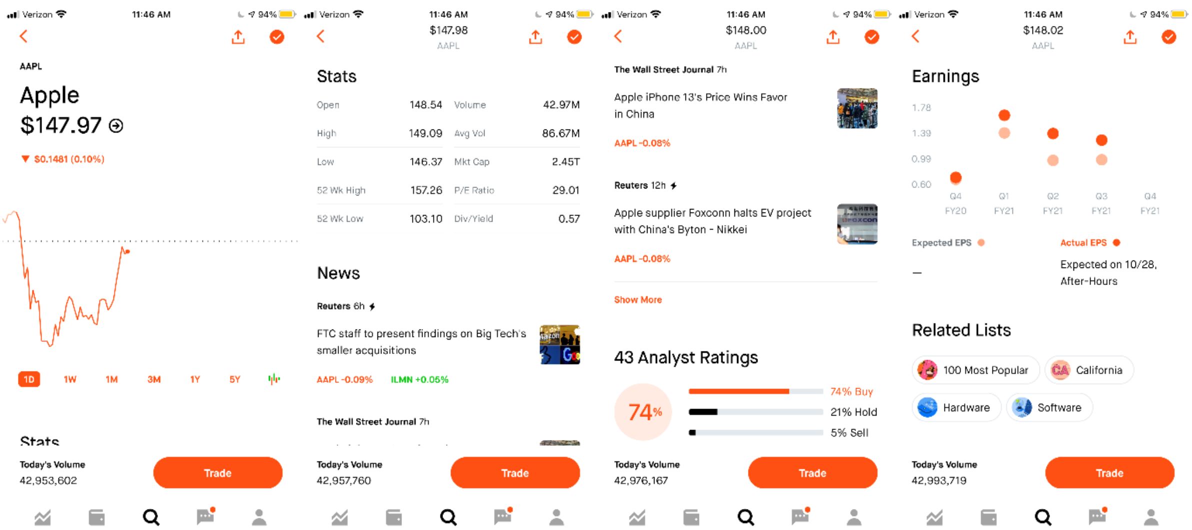


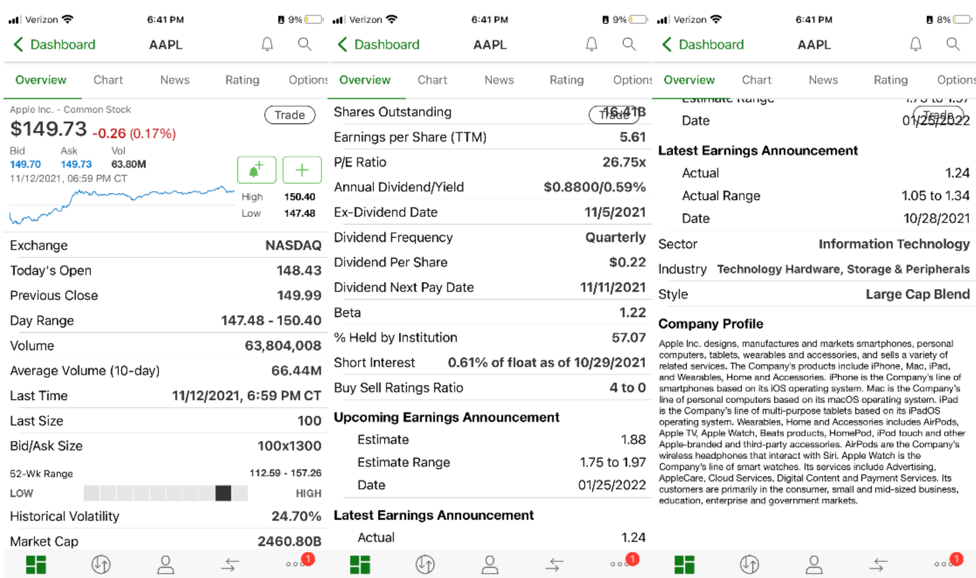
Figure 5 shows event study plots from using the two-stage least squares proxy variable approach developed in Freyaldenhoven et al. (2019). Panel A shows estimates from the positive five percent sample, and Panel B shows estimates from the negative five percent sample. The dependent variable is indicated above each plot. The event window t=0 (labeled "Notification" in the plots) is the first fifteen-minute window after a Robinhood push notification. The coefficient estimate at t-1 and t-2 is normalized to equal zero. The coefficient estimates on the remaining event windows measure the level of *Retail Reaction* (dependent variable) relative to the average level at t-1 and t-2. To facilitate interpretation of the magnitude of coefficient estimates, I have included the average level of *Retail Reaction* during the t-1 window next to the 'zero' reference line on the Y-axis.

Figure 6: Saliency of Earnings Information on Robinhood

Panel A: Robinhood Platform

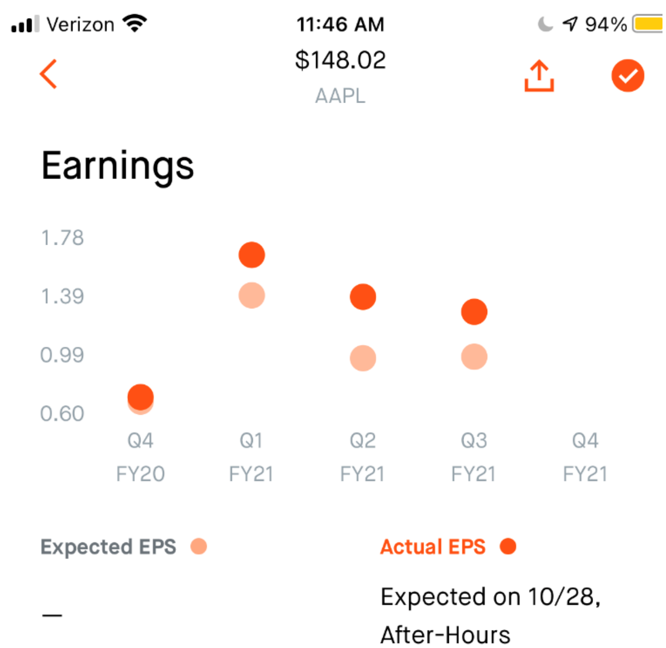


Panel B: TD Ameritrade Platform



This figure shows the user interface and information display of the Robinhood mobile app (Panel A) and TD Ameritrade mobile app (Panel B).

Figure 7: Earnings Chart on Robinhood



This figure shows how Robinhood displays earnings information.

Table 1: Descriptive Statistics for Primary Regression Variables

Panel A: Positive 5% Push Notification Sample

Variable	*N*	*Mean*	*Std. Dev.*	*P25*	*Median*	*P75*
Variables of Interest:						
Total Retail Trades	3,353,063	25.12	171.62	1	4	12
Retail Buy Trades	3,353,063	13.20	95.21	0	2	6
Retail Sell Trades	3,353,063	11.92	78.10	0	2	6
Retail Order Imbalance	3,353,063	0.29	56.84	-30.23	0	33.33
RH Earnings Surprise	452,568	0.03	0.43	-0.17	0.05	0.27
Academic Earnings Surprise	453,664	-0.01	0.12	-0.01	0.00	0.06
$Return_{t+1,t+5}$	532,244	0.00	0.14	-0.05	-0.01	0.05

(Continued)

Table 1: Descriptive Statistics for Primary Regression Variables

Panel B: Negative 5% Push Notification Sample

Variable	*N*	*Mean*	*Std. Dev.*	*P25*	*Median*	*P75*
Variables of Interest:						
Total Retail Trades	3,490,085	26.10	179.76	1	4	12
Retail Buy Trades	3,490,085	14.20	99.99	0	2	6
Retail Sell Trades	3,490,085	11.88	81.44	0	2	6
Retail Order Imbalance	3,490,085	3.07	56.98	-23.65	0	33.33
RH Earnings Surprise	475,864	0.03	0.43	-0.18	0.04	0.27
Academic Earnings Surprise	476,588	-0.01	0.14	-0.01	0.00	0.01
$Return_{t+1,t+5}$	552,796	0.00	0.13	-0.05	0.00	0.05

This table presents descriptive statistics for my primary variables of interest. Panel A presents descriptive statistics from the positive five percent sample, and Panel B presents descriptive statistics for the negative five percent sample.

Table 2: The Impact of Information Saliency on the Use of Earnings Information

Panel A: Positive 5% Push Notification Sample

Dependent variable:	*(1)* *Retail Order Imbalance*	*(2)* *Retail Order Imbalance*	*(3)* *Adjusted Retail Order Imbalance*	*(4)* *Adjusted Retail Order Imbalance*
Post2	-8.881***	-8.846***	-15.39***	-15.42***
	(-23.05)	(-23.16)	(-25.91)	(-26.27)
Post2*Std. RH Earnings Surprise	0.365**	0.341**	0.546**	0.684***
	(2.207)	(2.067)	(2.344)	(2.895)
Post2*Std. $\text{Return}_{t-5,t-1}$		0.0207		-1.501***
		(0.133)		(-3.981)
Post2*Std. $\text{Return}_{t-63,t-1}$		-0.306*		-1.392***
		(-1.692)		(-3.883)
Post2*Std. $\text{Return}_{t-253,t-1}$		0.531***		-0.166
		(3.901)		(-0.417)
Post2*Std. Analyst Buy %		-0.700***		0.226
		(-3.303)		(0.690)
Post2*Std. Analyst Sell %		-0.0783		-0.421
		(-0.445)		(-1.275)
Stock-Day Fixed Effects	Included	Included	Included	Included
Time of Day Fixed Effects	Included	Included	Included	Included
R^2	0.055	0.055	0.692	0.693
N	451,693	449,308	451,693	449,308

(Continued)

Table 2: The Impact of Information Saliency on the Use of Earnings Information

Panel B: Negative 5% Push Notification Sample

Dependent variable:	*(1)* *Retail Order Imbalance*	*(2)* *Retail Order Imbalance*	*(3)* *Adjusted Retail Order Imbalance*	*(4)* *Adjusted Retail Order Imbalance*
Post2	9.374***	9.373***	11.40***	11.41***
	(23.00)	(23.33)	(25.13)	(25.33)
Post2*Std. RH Earnings Surprise	-0.587***	-0.578***	-0.550***	-0.579***
	(-3.405)	(-3.304)	(-2.923)	(-2.961)
Post2*Std. $\text{Return}_{t-5,t-1}$		0.0102		-0.367*
		(0.0598)		(-1.662)
Post2*Std. $\text{Return}_{t-63,t-1}$		0.452**		0.567***
		(2.377)		(2.865)
Post2*Std. $\text{Return}_{t-253,t-1}$		-0.472***		-0.0194
		(-3.167)		(-0.0696)
Post2*Std. Analyst Buy %		1.121***		0.747***
		(4.949)		(3.091)
Post2*Std. Analyst Sell %		0.547***		0.562***
		(2.820)		(2.739)
Stock-Day Fixed Effects	Included	Included	Included	Included
Time of Day Fixed Effects	Included	Included	Included	Included
R^2	0.077	0.077	0.482	0.483
N	474,142	471,906	474,142	471,906

This table presents the results from estimating Equation 4 using OLS regression with earnings surprise measured as it appears visually on Robinhood. Panel A presents the results from the positive five percent sample, and Panel B presents the results for the negative five percent sample. The dependent variable is either *Retail Order Imbalance* or *Adjusted Retail Order Imbalance* as defined in Section 4. The primary coefficient estimate of interest is the interaction term *Post2*Std. RH Earnings Surprise*. I Include controls for the non-earnings information that is available on Robinhood and interact these controls with *Post2*. These include *Std.* $\textit{Return}_{t-5,t-1}$, *Std.* $\textit{Return}_{t-63,t-1}$, and *Std.* $\textit{Return}_{t-253,t-1}$, *Std. Analyst Buy %*, and *Std. Analyst Sell %* as defined in Section 4. All the independent variables except for *Post2* are standardized to have a mean equal to zero and standard deviation equal to one. The main effects of *Std. RH Earnings Surprise* and the other control variables are subsumed by the Stock-Day fixed effects. I include stock-day and time of day fixed effects as indicated but do not report the coefficients. The table reports OLS coefficient estimates and (in parentheses) *t*-statistics based on robust standard errors clustered by stock and date. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% p-levels (two-tailed), respectively.

Table 3: The Impact of Information Display on the Use of Earnings Information

Panel A: Positive 5% Push Notification Sample

Dependent variable:	*(1)* *Retail Order Imbalance*	*(2)* *Retail Order Imbalance*	*(3)* *Adjusted Retail Order Imbalance*	*(4)* *Adjusted Retail Order Imbalance*
Post2	-8.883***	-8.844***	-15.38***	-15.42***
	(-23.06)	(-23.16)	(-25.92)	(-26.25)
Post2*Std. Academic Earnings Surprise	0.104	0.0836	0.0432	0.101
	(0.511)	(0.412)	(0.192)	(0.446)
Post2*Std. $\text{Return}_{t-5,t-1}$		0.0104		-1.510***
		(0.0673)		(-4.006)
Post2*Std. $\text{Return}_{t-63,t-1}$		-0.291		-1.353***
		(-1.614)		(-3.802)
Post2*Std. $\text{Return}_{t-253,t-1}$		0.552***		-0.137
		(4.019)		(-0.346)
Post2*Std. Analyst Buy %		-0.715***		0.198
		(-3.366)		(0.603)
Post2*Std. Analyst Sell %		-0.0763		-0.419
		(-0.433)		(-1.273)
Stock-Day Fixed Effects	Included	Included	Included	Included
Time of Day Fixed Effects	Included	Included	Included	Included
R^2	0.055	0.055	0.692	0.693
N	452,568	450,045	452,568	450,045

(Continued)

Table 3: The Impact of Information Display on the Use of Earnings Information

Panel B: Negative 5% Push Notification Sample

Dependent variable:	*(1)* *Retail Order Imbalance*	*(2)* *Retail Order Imbalance*	*(3)* *Adjusted Retail Order Imbalance*	*(4)* *Adjusted Retail Order Imbalance*
Post2	9.370***	9.373***	11.39***	11.40***
	(23.06)	(23.35)	(25.19)	(25.36)
Post2*Std. Academic Earnings Surprise	-0.416*	-0.414*	-0.390*	-0.403*
	(-1.846)	(-1.860)	(-1.734)	(-1.792)
Post2*Std. $Return_{t-5,t-1}$		0.0193		-0.358
		(0.113)		(-1.629)
Post2*Std. $Return_{t-63,t-1}$		0.429**		0.544***
		(2.275)		(2.774)
Post2*Std. $Return_{t-253,t-1}$		-0.485***		-0.0334
		(-3.249)		(-0.120)
Post2*Std. Analyst Buy %		1.146***		0.772***
		(5.071)		(3.209)
Post2*Std. Analyst Sell %		0.537***		0.552***
		(2.760)		(2.682)
Stock-Day Fixed Effects	Included	Included	Included	Included
Time of Day Fixed Effects	Included	Included	Included	Included
R^2	0.077	0.077	0.481	0.482
N	474,956	472,620	474,956	472,620

This table presents the results from estimating Equation 4 using OLS regression with earnings surprise measured using the academic transformation. Panel A presents the results from the positive five percent sample, and Panel B presents the results for the negative five percent sample. The dependent variable is either *Retail Order Imbalance* or *Adjusted Retail Order Imbalance* as defined in Section 4. The primary coefficient estimate of interest is the interaction term *Post2*Std. Academic Earnings Surprise*. I Include controls for the non-earnings information that is available on Robinhood and interact these controls with *Post2*. These include *Std.* $Return_{t-5,t-1}$, *Std.* $Return_{t-63,t-1}$, and *Std.* $Return_{t-253,t-1}$, *Std. Analyst Buy %*, and *Std. Analyst Sell %* as defined in Section 4. All the independent variables except for *Post2* are standardized to have a mean equal to zero and standard deviation equal to one. The main effects of *Std. Academic Earnings Surprise* and the other control variables are subsumed by the Stock-Day fixed effects. I include stock-day and time of day fixed effects as indicated but do not report the coefficients. The table reports OLS coefficient estimates and (in parentheses) *t*-statistics based on robust standard errors clustered by stock and date. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% p-levels (two-tailed), respectively.

Table 4: The Impact of Information Display on the Use of Earnings Information

Panel A: Positive 5% Push Notification Sample

Dependent variable:	*(1)* *Retail Order Imbalance*	*(2)* *Retail Order Imbalance*	*(3)* *Adjusted Retail Order Imbalance*	*(4)* *Adjusted Retail Order Imbalance*
Post2	-8.883***	-8.847***	-15.39***	-15.42***
	(-23.05)	(-23.17)	(-25.92)	(-26.27)
Post2*Std. RH Earnings Surprise	0.378**	0.359**	0.613**	0.746***
	(2.132)	(2.026)	(2.442)	(2.930)
Post2*Std. Academic Earnings Surprise	-0.0340	-0.0461	-0.181	-0.169
	(-0.155)	(-0.212)	(-0.748)	(-0.689)
Post2*Std. $Return_{t-5,t-1}$		0.0201		-1.501***
		(0.129)		(-3.980)
Post2*Std. $Return_{t-63,t-1}$		-0.305*		-1.390***
		(-1.686)		(-3.878)
Post2*Std. $Return_{t-253,t-1}$		0.532***		-0.165
		(3.902)		(-0.415)
Post2*Std. Analyst Buy %		-0.700***		0.225
		(-3.303)		(0.689)
Post2*Std. Analyst Sell %		-0.0789		-0.424
		(-0.448)		(-1.286)
Stock-Day Fixed Effects	Included	Included	Included	Included
Time of Day Fixed Effects	Included	Included	Included	Included
R^2	0.055	0.055	0.692	0.693
N	451,689	449,304	451,689	449,304

(Continued)

Table 4: The Impact of Information Display on the Use of Earnings Information

Panel B: Negative 5% Push Notification Sample

Dependent variable:	*(1)* *Retail Order Imbalance*	*(2)* *Retail Order Imbalance*	*(3)* *Adjusted Retail Order Imbalance*	*(4)* *Adjusted Retail Order Imbalance*
Post2	9.374***	9.373***	11.40***	11.41***
	(23.01)	(23.33)	(25.13)	(25.33)
Post2*Std. RH Earnings Surprise	-0.502***	-0.492***	-0.469**	-0.497**
	(-2.755)	(-2.669)	(-2.342)	(-2.394)
Post2*Std. Academic Earnings Surprise	-0.237	-0.240	-0.222	-0.227
	(-0.978)	(-1.007)	(-0.918)	(-0.940)
Post2*Std. $Return_{t-5,t-1}$		0.0123		-0.365*
		(0.0723)		(-1.652)
Post2*Std. $Return_{t-63,t-1}$		0.453**		0.568***
		(2.385)		(2.873)
Post2*Std. $Return_{t-253,t-1}$		-0.469***		-0.0168
		(-3.151)		(-0.0601)
Post2*Std. Analyst Buy %		1.120***		0.746***
		(4.946)		(3.087)
Post2*Std. Analyst Sell %		0.543***		0.559***
		(2.804)		(2.722)
Stock-Day Fixed Effects	Included	Included	Included	Included
Time of Day Fixed Effects	Included	Included	Included	Included
R^2	0.077	0.077	0.481	0.483
N	474,142	471,906	474,142	471,906

This table presents the results from estimating Equation 4 using OLS regression with both measures of earnings surprise included. Panel A presents the results from the positive five percent sample, and Panel B presents the results for the negative five percent sample. The dependent variable is either *Retail Order Imbalance* or *Adjusted Retail Order Imbalance* as defined in Section 4. The primary coefficient estimates of interest are the interaction terms *Post2*Std. RH Earnings Surprise* and *Post2*Std. Academic Earnings Surprise*. I Include controls for the non-earnings information that is available on Robinhood and interact these controls with *Post2*. These include *Std.* $Return_{t-5,t-1}$, *Std.* $Return_{t-63,t-1}$, and *Std.* $Return_{t-253,t-1}$, *Std. Analyst Buy %*, and *Std. Analyst Sell %* as defined in Section 4. All the independent variables except for *Post2* are standardized to have a mean equal to zero and standard deviation equal to one. The main effects of *Std. RH Earnings Surprise, Std. Academic Earnings Surprise* and the other control variables are subsumed by the Stock-Day fixed effects. I include stock-day and time of day fixed effects as indicated but do not report the coefficients. The table reports OLS coefficient estimates and (in parentheses) *t*-statistics based on robust standard errors clustered by stock and date. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% p-levels (two-tailed), respectively.

Table 5: The Impact of RH's Digital Engagement Practices on Retail Investor Informativeness

Panel A: Positive 5% Push Notification Sample

Market-adjusted Return$_{t+1,t+5}$ as dependent variable:	*(1)*	*(2)*	*(3)*	*(4)*
Post2	0.0280	0.0167	0.0170	0.00709
	(0.672)	(0.469)	(0.404)	(0.196)
Post2*Std. Retail Order Imbalance	0.0653*	0.0673*		
	(1.714)	(1.753)		
Post2*Std. Adjusted Retail Order Imbalance			0.0452*	0.0519**
			(1.926)	(2.220)
Std. Retail Order Imbalance	-0.0439	Monthly		Monthly
	(-1.493)			
Std. Adjusted Retail Order Imbalance			-0.144***	
			(-3.618)	
Return$_{t-5,t-1}$	-4.203***	Monthly	-4.219***	Monthly
	(-2.887)		(-2.898)	
Return$_{t-63,t-1}$	0.0350	Monthly	0.0199	Monthly
	(0.141)		(0.0801)	
Return$_{t-253,t-1}$	-0.0116	Monthly	-0.0137	Monthly
	(-0.170)		(-0.200)	
lnMVE	-0.132***	Monthly	-0.158***	Monthly
	(-2.610)		(-2.897)	
lnMB	0.0207	Monthly	0.0250	Monthly
	(0.209)		(0.252)	
Main Effects Allowed to Vary Monthly	No	Yes	No	Yes
Year-Month Fixed Effects	Included	Included	Included	Included
Time of Day Fixed Effects	Included	Included	Included	Included
R^2	0.008	0.022	0.008	0.023
N	527,934	527,934	527,934	527,934

(Continued)

Table 5: The Impact of RH's Digital Engagement Practices on Retail Investor Informativeness
Panel B: Negative 5% Push Notification Sample

Market-adjusted *Return*$_{t+1,t+5}$ as dependent variable*:*	*(1)*	*(2)*	*(3)*	*(4)*
Post2	-0.00861	-0.00655	-0.00913	-0.00854
	(-0.312)	(-0.253)	(-0.326)	(-0.326)
Post2*Std. Retail Order Imbalance	-0.00187	-0.00484		
	(-0.0560)	(-0.147)		
Post2*Std. Adjusted Retail Order Imbalance			0.0139	0.0154
			(0.500)	(0.566)
Std. Retail Order Imbalance	0.0232	Monthly		Monthly
	(0.772)			
Std. Adjusted Retail Order Imbalance			0.0165	
			(0.463)	
Return$_{t-5,t-1}$	-3.956***	Monthly	-3.960***	Monthly
	(-3.916)		(-3.914)	
Return$_{t-63,t-1}$	-0.171	Monthly	-0.173	Monthly
	(-1.010)		(-1.021)	
Return$_{t-253,t-1}$	-0.0649	Monthly	-0.0655	Monthly
	(-0.995)		(-1.001)	
lnMVE	0.0274	Monthly	0.0240	Monthly
	(0.688)		(0.583)	
lnMB	0.234***	Monthly	0.234***	Monthly
	(2.710)		(2.715)	
Main Effects Allowed to Vary Monthly	No	Yes	No	Yes
Year-Month Fixed Effects	Included	Included	Included	Included
Time of Day Fixed Effects	Included	Included	Included	Included
R^2	0.023	0.038	0.023	0.038
N	548,087	548,087	548,087	548,087

This table presents the results from estimating Equation 5 using OLS. Panel A presents the results from the positive five percent sample, and Panel B presents the results for the negative five percent sample. The dependent variable is *Market-adjusted Return*$_{t+1,t+5}$ as defined in Section 4. The primary coefficient estimates of interest are the interaction terms *Post2*Std. Retail Order Imbalance* and *Post2*Std. Adjusted Retail Order Imbalance*. I Include controls for factors known to predict future returns. These include *Return*$_{t-5,t-1}$, *Return*$_{t-63,t-1}$, and *Return*$_{t-253,t-1}$, *lnMVE,* and *lnMB* as defined in Section 4. The independent variables of interest, *Std. Retail Order Imbalance* and *Std. Adjusted Retail Order Imbalance*, are standardized to have a mean equal to zero and standard deviation equal to one. In Columns 2 and 4 for each panel, I allow the coefficient on the main effects of the independent variables to vary at the monthly level. I do not report the coefficient estimates for variables that I estimate on a monthly level. I include year-month and time of day fixed effects as indicated but do not report the coefficients. The table reports OLS coefficient estimates and (in parentheses) *t*-statistics based on robust standard errors clustered by stock and date. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% p-levels (two-tailed), respectively.