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

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This draft: January 18, 2022

Abstract

I investigate how retail brokerages' digital engagement practices (e.g., push notifications and content curation) 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 relative to non-retail investor trading. I then exploit the discontinuous increase in the proportion of retail investors trading on Robinhood with similar information sets to examine whether Robinhood's content curation practices induce retail investors to incorporate earnings information in their trades. I find that retail investors trading on Robinhood after push notifications use earnings surprise information in their trades. Notably, Robinhood displays earnings information in a way that an investor's visual perception of earnings surprise 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. A difference-in-differences analysis around the introduction of earnings information on Robinhood as well as placebo analyses using Robinhood outages and an alternative notification threshold support these inferences. Lastly, I find that the influence of these digital engagement practices does not have a meaningful impact—positive nor negative—on aggregate retail investor informativeness.

Keywords: Retail Investors, Digital Engagement Practices, Push Notifications, Information Processing, Accounting Information, Visual Information

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* I am thankful for advice and mentorship from my dissertation committee, Paul Hribar (co-chair), Clare Wang (co-chair), Scott Asay, Jon Garfinkel, and Cristi Gleason. I am indebted to my fellow PhD students (past and present) for countless discussions that helped develop how I think about research and the world around me. I thank Betty Liu for thought-provoking conversations about retail investors and for sharing data on Robinhood outages.

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"[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 two notable digital engagement practices: (i) push notifications and (ii) content curation.[1]

[1] The definition of content curation that I am referring to is, "Content Curation is the act of discovering, gathering, and presenting content that surrounds specific subject matter."

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. Robinhood's publicly stated reason for providing notifications aligns with the investment monitoring example. In their blog post announcing notifications as a new feature, Robinhood states *"If you aren't always monitoring the market or keeping an eye on your portfolio, you might miss out on an opportunity or that breaking news story. With Smart Notifications, you won't miss a beat"* (Robinhood, 2016).

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).[2] 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. Using push notifications as a shock to the number of retail investors viewing information available through Robinhood, I next examine how content curation practices impact the information that retail investors use to trade. The second Robinhood feature that I use is their markedly different content curation practices relative to competing brokerages. Specifically, Robinhood provides less information than other retail brokerages and displays the information using data visualization techniques that ease its interpretation (Figure 8). Using a set of variables that reconstruct the information available through Robinhood, I test whether Robinhood's content curation affects the incorporation of earnings information into investors' trading decisions.

Lastly, to better understand how one specific aspect of content curation influences retail investors, I utilize a third feature enabling me to test whether the specific manner in which information is displayed impacts retail investor trading independent from the underlying information itself. Robinhood displays a firm's earnings information as a scatterplot of actual and expected earnings per share (i.e., EPS) values with the range of the Y-axis being a function of the minimum and maximum EPS values over the last four quarters (Figure 9). Relative to an earnings surprise measure commonly used in the accounting literature (i.e., scaling unexpected earnings by share price), Robinhood's visual display of earnings information can distort the perceived magnitude of earnings news.

[2] Robinhood also sends push notifications when stock prices move ten percent intraday. I focus on the sample of five percent notifications because: (i) five percent notifications are turned on by default, (ii) they are significantly more common, and (iii) the pre-event period is not confounded by an earlier notification (i.e., five percent notifications are sent out prior to ten percent notifications). Stock price notifications are discussed on the Robinhood website here: https://robinhood.com/us/en/support/articles/stock-price-alerts/.

My research design 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.[3] 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).[4] To correct for observable trends in retail investor activity prior to the push notification threshold, I use the two-stage least squares proxy variable approach developed in Freyaldenhoven, Hansen, and Shapiro (2019).[5] 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). In 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 event

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[3] This intraday event study design is similar to a regression discontinuity design comparing investor reactions to stock returns just below and just above a 5% threshold. However, the event study design also accounts for how close an event window is to the push notification threshold. Accounting for both the stock return and temporal aspects of my setting are important for two primary reasons. First, stock returns can revert below 5% after triggering a push notification. Since the notification has already been sent to investors, this time period is still 'treated' even if the current stock return is below 5%. Second, the aggregate response to push notifications is expected to diminish as time passes even if the stock return remains flat after the push notification.

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

[5] 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.

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 likely 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 primarily owners of the stock, enabling them to either buy more shares or sell the shares they own (Barber and Odean, 2008).[6] 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.

[6] When examining retail investors who do not already own the stock, attention impacts buying behavior more than selling behavior due to the asymmetric costs of taking a long versus short position in the stock.

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 approximately 25% 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. In contrast, buying activity accounts for 83% of the increase in trades following negative notifications.[7] Additionally, results from placebo event studies using (i) an intraday return of four percent and (ii) Robinhood outages support the attribution of my results to Robinhood push notifications. 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 impact of content curation practices on the use of earnings information signals by retail investors. Certain content curation practices, such as the simplified and visual information display that Robinhood is known for, might benefit retail investors by nudging them to process important, value relevant information, which they might otherwise neglect or underweight in their investment decision (e.g., Nekrasov, Teoh, and Wu, 2022). This

[7] Due to significant heterogeneity in the amount of retail trading activity across stocks, expressing effect sizes as percentages is more representative of my results than expressing effects as the number of retail trades. To support my choice to express results in percentage terms, I run my analyses within quintiles of firms sorted on pre-period retail investor trades (untabulated). Across all five quintiles I find similar effect estimates when expressed as percentages but monotonically increasing effect estimates when expressed as the number of retail trades. Nonetheless, in the fifteen minutes after a positive push notification, there are eight additional retail trades and six of these trades are sales (on average). Similarly, after a negative push notification, there are six additional retail trades and five of these trades are purchases (on average).

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 and easily interpretable. Furthermore, a necessary condition for content curation to benefit investors is for the information to be value relevant. If irrelevant signals are made salient by content curation practices, 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).

A challenge in identifying the information used by retail investors in their trading decisions is the disperse and unobservable nature of their information set. I overcome this impediment in two ways. First, I leverage my previous results showing that push notifications act as a temporary shock to the number of retail investors who are trading on Robinhood. Supported by the institutional details of my setting as well as a host of additional analyses, I assume that the push notifications isolate retail investor activity taking place on Robinhood from retail investor activity across all brokerages, allowing me to compare the use of information by investors using Robinhood to the use of information by investors using all brokerages.[8] Second, I use a variable that captures Robinhood's unique display of earnings information, helping identify Robinhood as the source of information as opposed to another unobservable information source.

I find evidence consistent with Robinhood's content curation practices impacting the information retail investors use to trade. Using an earnings surprise measure created to reflect how Robinhood uniquely displays earnings information, I find that a one standard deviation increase in earnings surprise moderates the net selling reaction to positive push notifications by

[8] All the analyses in Section 4.1 can be viewed as providing evidence to validate this assumption. Further, this assumption is discussed in more detail in Section 4.2 along with additional tests supporting its plausibility.

about 6%. This effect size is economically meaningful compared to other information used by retail investors as it is approximately 65% 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 8%, an effect size slightly larger in magnitude than a one standard deviation increase in the past year's returns. Overall, Robinhood's content curation practices increase the use of earnings information by retail investors.

Next, I examine whether retail investors use information as it is displayed to them 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 commonly transform it into a value relevant information signal. When I repeat the previous tests with the inclusion of unexpected earnings scaled by stock price, I consistently find that retail investors *do not* use this information in their trading decisions. However, they continue to use the visual Robinhood earnings surprise information. These results indicate that how brokerages display information impacts investors' information acquisition and integration activities.

My final set of analyses examine the influence of Robinhood's digital engagement practices on the aggregate informativeness of retail investor trades. To assess the effect 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 slightly 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. One concern with this analysis is whether pre-notification trading is the proper benchmark to measure the influence of push notifications on investor informativeness against. While I do not think it is a perfect benchmark to make inferences regarding individual trading performance, I do think it is a useful benchmark that we can learn something about aggregate informativeness from. Overall, I conclude that digital engagement practices do not have a meaningful impact—positive nor negative—on aggregate retail investor informativeness.

My paper contributes to several streams of literature. First, in contrast to conclusions in Blankespoor, deHaan, Wertz, and Zhu (2019) and Michels (2021) that individual investors disregard earnings information in favor of information on past returns, I conclude that retail investors use earnings information when it is displayed in a simple, visually oriented fashion. A likely explanation for why my conclusion differs from these other papers is that retail investors do not use "unexpected earnings scaled by stock price" as an information signal. Indeed, I also find that retail investors do not use "unexpected earnings scaled by stock price" to trade. Rather, my results suggest that retail investors use some other transformation of unexpected earnings that might vary based on how the information is displayed to them.

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 guide investors to use 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) and Friedman and Zeng (2021) examine how Robinhood investors trade around earnings announcements. My paper adds to this budding literature by examining several of Robinhood's digital engagement practices and their impact on retail investor trading and information processing.

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 the impact of 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, Robinhood's content curation practices decrease information acquisition and integration costs by simplifying the cognitive processing required by investors to use value relevant information.

2. Institutional Details

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.[9]

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

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 Content Curation Practices

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.*"

Two primary aspects of Robinhood's content curation practices standout when compared with other brokerages. First, 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. Limiting the amount of information easily accessible to investors might hurt trading performance 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).

Second, Robinhood displays information using data visualization techniques that ease its interpretability and reduces cognitive overload (Figure 8 Panel A). In contrast, TD Ameritrade presents information as a list of text that does not include data visualizations (Figure 8 Panel B). Psychology research shows that visuals are more salient and vivid than text, resulting in increased awareness and cognitive processing of visuals over text (e.g., Fiske and Taylor, 2016). Thus, Robinhood's visual display of earnings information is more likely to be used by retail investors than the earnings information displayed by other brokerages. Furthermore, individuals have the ability to recall visuals that were displayed to them for only a fraction of a second, suggesting that Robinhood's earnings chart may factor into investor trading decisions even if the investor only observed the chart momentarily (Potter, Wyble, Hagmann, and McCourt, 2014).

I focus on the use of earnings information in examining the impact of content curation practices on retail investor information processing and trading. I do so for three primary reasons. First, earnings information is known to be value relevant (e.g., Kothari, 2001), providing an *ex ante* justification for why it should be used in trading decisions. Second, even though earnings information is value relevant, recent studies find that retail investors neglect earnings information when making trading decisions (e.g., Blankespoor et al., 2019, Michels, 2021). Based on institutional details, I believe my setting offers a particularly powerful test of whether retail investors use earnings information. Lastly, several features of my setting allow for better identification of earnings information use relative to other information available on Robinhood.

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).[10] 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

[10] 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.

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. 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. While I do not have the granular data required to estimate how understated these effects are within my sample, aggregate statistics can provide some context. During June 2020, Robinhood reported having 4.21 million daily average revenue trades (i.e., DART), transacting 33% of all DART reported by Charles Schwab, E*Trade, Interactive Brokers, and TD Ameritrade.

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 intraday changes in trading activity. 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 jump 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. This pre-trend in *Retail Reaction* confounds my estimates 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 an observed 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: $\textit{Retail Reaction}_{i,t} = \sum\beta_t \textit{Event Window}_{i,t} + \gamma \textit{Fitted Non-Retail Trades}_{i,t}$

$+ \textit{Fixed Effects} + \varepsilon_{i,t}$ (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, Equation 3 also excludes the *Event Window(t-2)* indicator variable since an *Event Window* indicator still needs to be dropped for identification of the fixed effects.[11]

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

[11] All analyses using the Freyaldenhoven et al. (2019) methodology are implemented in Stata using the *xtevent* package from Freyaldenhoven et al. (2021).

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, providing evidence consistent with *Non-Retail Trades* being an appropriate proxy variable. 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 jump 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 on average. Compared to the 29 retail trades occurring, on average, in the fifteen minutes before a notification, retail trading increases by 27%. Looking at buy and sell trades separately shows that the increase in total retail investor trading is driven by an increase in retail investor selling activity. A relatively larger increase in selling than buying is also observed in the retail order imbalance plot. Retail order imbalance drops from 6% net buys at t-1 to approximately -10% (i.e., 10% net sells) immediately after a notification. Interestingly, retail trading activity reverts to its pre-notification level within about sixty minutes, consistent with push notifications having an immediate but short-lived impact.

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 on average. 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 buying activity. On average, 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, moving from 2% net selling activity to 10% net buying activity.

One potential concern for attributing the change in retail investor activity at the +/- 5% threshold to Robinhood push notifications is that investor behavior may change at +/- 5% because it is a round number and not because of the notification. To provide evidence that round number bias does not drive my results, I examine retail trading activity around a placebo +/- 4% threshold. This test repeats the analysis in Figure 5 with two differences. First, the sample consists of stocks who had an intraday return of at least +/- 4% but less than +/- 5%. I exclude stocks that eventually reached the actual push notification threshold to ensure the post-period does not include the effects of push notifications. Second, I use the +/- 4% threshold when creating event windows.

Figure 6 presents the results of the 4% placebo analysis for total retail trades. The inferences based on the other measures of retail investor activity are qualitatively the same, so I do not report those figures for brevity.[12] At both the positive and negative placebo thresholds there is not a meaningful increase in retail investor activity. Although the coefficients for t=0 (labeled 'Placebo Notification" in the plots) are statistically significant, the estimated coefficients are approximately 85% smaller than the equivalent estimates at the actual push notification threshold. Based on these results, I conclude that a round number bias does not drive the change in retail investor activity around the Robinhood push notification threshold.

[12] These results are available upon request.

An additional concern for attributing my results to Robinhood push notifications is that retail investors could be reacting to notifications from other brokerages, either because investors tend to set custom price alerts at 5% or the other brokerages could also send notifications around 5% price movements. I have checked the notification systems of the other major retail brokerages and none of them had an option to receive notifications at 5%, providing qualitative evidence that the effect I document is attributable to Robinhood. Additionally, I examine whether there is a change in retail activity at the 5% threshold during Robinhood outages to provide quantitative evidence. If my results document the impact of Robinhood push notifications, then there should not be a change in retail investor activity when it is impossible to trade on Robinhood. Further, this test provides additional evidence that my results are not driven by round number bias. I identify the start and end times of Robinhood outages using data from downdetector.com and examine only stocks that crossed the 5% threshold during these outage events.[13] The results of this analysis are presented in Figure 7.[14] The event study plots show that there is not a significant change in retail investor activity at the 5% threshold when investors cannot trade on Robinhood. These results provide compelling evidence that the results I document in my primary analyses are attributable to Robinhood push notifications.

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 approximately 25% in the minutes following a notification. Further, notifications induce net selling behavior after positive push

[13] Other papers examining retail investor activity have also used downdetector.com to identify brokerage outages (e.g., Liu, 2021; Eaton, Green, Roseman, and Wu, 2021).

[14] I only present the results for total retail trades as the inferences based on the other measures of retail investor activity are the same. Results for the other measures are available upon request.

notifications and net buying behavior after negative push notifications. Additional analyses using a 4% placebo threshold and Robinhood outages provide evidence against alternative explanations.

4.2 Content Curation Practices and Retail Investor Use of Earnings Information

My next analysis examines whether Robinhood's content curation practices impact retail investors' use of earnings information. Relative to other brokerage platforms, Robinhood uses data visualizations to display firm information on a simple, easily accessible interface. These design choices make earnings information more noticeable and easily interpretable (e.g., Shepard, 1967; Hockley, 2008; Fiske and Taylor, 2016). Figure 8 provides examples of the Robinhood and TD Ameritrade mobile apps. Looking at these examples, earnings information is likely more prominent to retail investors in the Robinhood app, with less overall information and earnings information displayed visually using a chart.

Since the difference in retail investor behavior between the pre-notification period and post-notification period is driven by investors trading on Robinhood,[15] I measure the impact of Robinhood's content curation practices by examining how the association between a stock's most recent earnings surprise and retail order imbalance changes in the post-notification period relative to the pre-notification period. Specifically, to test whether Robinhood's content curation practices induce retail investors to incorporate earnings information in their trading decisions, I estimate the following model using ordinary least squares (i.e., OLS) regression:

[15] This is an assumption of my research design that is strongly supported by the institutional details of my setting and is validated by the analyses in Section 4.1 as well as additional analyses later in Section 4.2.

$$Retail\ Order\ Imbalance_{i,t} = \beta\, Post_{i,t} * Std.\ RH\ Earnings\ Surprise_i + \sum \gamma_k\, Post_{i,t} * Std.\ RH\ Info\ Set_i + \gamma\, Post_{i,t} + \sum \gamma_k\, Std.\ RH\ Info\ Set_i + Fixed\ Effects + \varepsilon_{i,t} \quad (4)$$

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, I calculate *Adjusted Retail Order Imbalance* as *Retail Order Imbalance - γFitted Non-Retail Trades* where γ is the estimated coefficient from Equation 3 and *Fitted Non-Retail Trades* is the fitted value from Equation 2.[16] Thus, *Adjusted Retail Order Imbalance* captures retail trading behavior that is distinct from non-retail trading behavior.

Post 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 excluded from the analysis to focus on a tight setting with event windows that are most similar to one another. *RH Earnings Surprise* is a proxy for how retail investors visually perceive the previous quarter's earnings surprise as displayed on Robinhood. I provide an example of an earnings chart displayed on Robinhood in Figure 9. Specifically, Robinhood 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

[16] Since *Adjusted Retail Order Imbalance* is a 'generated regressor' and is thus an estimate itself, regressions including this variable use a bootstrap procedure to calculate standard errors (Wooldridge, 2002; Greene, 2017; Chen, Hribar, and Melessa, 2020).

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.

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., $Return_{t-5,t-1}$). 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. *Fixed Effects* continues to include *Stock-Day Fixed Effects* and *Time of Day Fixed Effects* as indicated.

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. Across all four columns, the coefficient estimate for *Post*Std. RH Earnings Surprise* is positive and significant. In conjunction with the lack of a significant association in the pre-period (Columns 1 and 3 main effect estimates), the positive coefficients on *Post*Std. RH Earnings Surprise* indicate that retail investors use earnings surprise information to trade after Robinhood push notifications. Based on the coefficient estimate of 0.34 in Column 1, a one standard deviation increase in *RH Earnings Surprise* moderates retail investor's net selling activity after a positive push notification by 6%. Compared to the primary reaction following notifications, this seems like a relatively small effect. However, compared to the coefficient estimates on the other information variables available through Robinhood, the effect is economically meaningful. For example, the effect of *RH Earnings Surprise* is about 64% 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, *Post*Std. RH Earnings Surprise*, is negative and significant. Additionally, in Columns 1 and 3, the coefficients on *Std. RH Earnings Surprise* are not statistically different from zero. The results indicate that retail investors incorporate earnings surprise information into their trades to a greater extent after push notifications, albeit in a contrarian fashion. Based on the coefficient estimates in Column 1, a one standard deviation increase in *Std. RH Earnings Surprise* moderates the net buying reaction to push notifications by 8%. This effect is moderately larger than the effect of $Return_{t-253,t-1}$.

There are several takeaways from Table 2. First, Robinhood's content curation practices increase the use of earnings information by retail investors as evidenced by greater associations (in absolute value) between net retail trading and an earnings surprise measure created to reflect the visual display of earnings on Robinhood after push notifications. Second, retail investors use earnings surprise information in a momentum-driven fashion (i.e., larger earnings surprises are a buying signal) after positive notifications but in a contrarian fashion (i.e., larger earnings surprises are a selling signal) after negative notifications. Lastly, the use of earnings information moderates the main response to push notifications for both positive and negative notifications.

In Table 2, I use a measure of earnings surprise constructed to mimic how Robinhood investors are likely to perceive the earnings information as displayed by Robinhood. Using an earnings surprise measure specific to Robinhood helps alleviate a concern that the results are driven by retail investors using a different information source that provides earnings information. 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, in Table 3, 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 by brokerages impacts retail investor trading independent from the underlying information signal.

In Table 3, I present results from estimating Equation 4 using both *RH Earnings Surprise* and *Academic Earnings Surprise*. In the positive (Panel A) and negative (Panel B) push notification samples, the coefficient estimates for *Post*Std. Academic Earnings Surprise* are statistically insignificant in all four columns, while the coefficient estimates for *Post*Std. RH Earnings Surprise* are statistically significant and of similar magnitude to the estimates in Table 2. These results have a couple of implications. First, the results suggest that retail investors *do not* use earnings surprises—as measured by accounting academics—in their trading decisions. This result potentially reconciles the conclusion in Blankespoor et al. (2019)—that retail investors do not use earnings information to trade even when they are given the information—with the conclusion of my paper—that retail investors use earnings information as it is displayed to them. Second, researchers examining the use of information (earnings or otherwise) by investors might increase the power of their tests by creating an information proxy that captures how the information is perceived by investors. Overall, the results from Tables 2 and 3 suggest that brokerages' content curation practices impact investors' information acquisition and integration activities.

Next, I examine whether retail investor earnings information use varies as time passes since the earnings were announced. At least two opposing forces could influence the intensity of retail investors' use of earnings information as it ages. First, as time passes, earnings grow "stale" and lose value relevance (e.g., Ball and Cuny, 2021; Liu and Moss, 2021).[17] If investors are aware of this effect, then their use of earnings information should decrease as time passes. Second, earnings announcements generate a significant amount of media coverage, increasing the awareness of earnings information (e.g., Blankespoor, deHaan, and Zhu, 2018; Blankespoor et al., 2019). However, as time passes, the awareness of earnings information likely declines and the memory of the earnings news fades, so the push notification about a large price movement triggers investors to reprocess and reevaluate the past news. This would manifest empirically as increased use of earnings information over time.

To examine the intensity of retail investors' use of earnings information as it ages, I estimate the specifications in Columns 2 and 4 of Table 3 partitioned by the number of days since the firm's most recent earnings announcement. Specifically, I create three subsamples based on whether a firm's most recent earnings announcement occurred (i) 1-30 days ago, (ii) 31-60 days ago, or (iii) 61-100 days ago. The results of this analysis are presented in Table 4. For the positive push notification sample (Panel A), I find that earnings information is used to a greater extent in the 31-60 and 61-100 subsamples than the 1-30 subsample. For example, the coefficient estimate for *Post*Std. RH Earnings Surprise* increases from -0.23 in the 1-30

[17] This is a common idea in the analyst literature. Analyst reports and forecasts become stale and less informative as new information and analyst reports are created (e.g., O'Brien, 1988).

subsample to 0.94 in the 31-60 subsample (Columns 1 and 2). Interestingly, the coefficient estimates are largest in the 31-60 subsample (Columns 2 and 4), although they are not statistically different than the 61-100 subsample coefficients (Columns 3 and 6). In contrast, for the negative push notification sample (Panel B), none of the subsample coefficients are statistically different from each other. At least for positive push notifications, retail investors seem to use earnings information to a greater degree when earnings information is not recently released. This result is consistent with the push notification and content curation practices triggering retail investors to reprocess earnings information that faded in memory.

My interpretation of the results in Tables 2-4 rely on two primary assumptions. First, that push notifications allow me to isolate retail investor activity taking place on Robinhood (i.e., post-period) and compare that to retail investor activity across all brokerages (i.e., pre-period). The analyses in Section 4.1 probe the validity of this first assumption and find evidence supporting its plausibility. Second, that Robinhood's unique display of earnings information rules out an omitted variable explanation where, after push notifications, investors are reacting to another source of earnings information that I do not observe or control for. Many of the previously discussed institutional details of my setting strongly support the plausibility of both assumptions. My next several analyses provide additional evidence supporting my inferences as well as the plausibility of these assumptions.

My first additional analysis uses a difference-in-differences design to exploit the institutional detail that Robinhood did not provide earnings information until January 17, 2017 (Robinhood, 2017).[18] Specifically, I limit this analysis to January 2017 and examine how the use

[18] The Robinhood blog post discussing the introduction of earnings information can be found here: https://blog.robinhood.com/news/2017/1/13/earnings-on-robinhood

of Robinhood's earnings information after push notifications changes following the introduction of earnings information on Robinhood. I conduct this analysis by creating *Post Earnings Introduction*, an indicator variable equal to one for dates after January 17, 2017, and equal to zero otherwise, and interacting it with all the variables in my primary information use analyses (e.g., Columns 2 and 4 of Table 3). Additionally, I refer to the post push notification indicator variable as *Post Notification* for this analysis.

Table 5 presents the results of my difference-in-differences analysis. The results examining the positive push notifications sample (Panel A) show a significant increase in the use of the Robinhood earnings surprise measure after Robinhood makes earnings information available. This is evidenced by a positive and statistically significant coefficient estimate on *Post Notification*Post Earnings Introduction*Std. RH Earnings Surprise.* In contrast, after the introduction of Robinhood earnings information, there is not a significant change in the use of the academic earnings surprise measure. Further, the lack of a significant coefficient on *Post Notification*Std. RH Earnings Surprise* provides compelling placebo evidence since it is impossible for retail investors to react to information that does not yet exist. The negative push notification results (Panel B) provide the same inferences. Overall, the results from my difference-in-differences analysis around the introduction of earnings information on Robinhood support my inference that content curation practices influence the information that retail investors use to trade.

My second additional analysis uses the Robinhood outage sample previously used in Figure 7. My main inferences rely on the coefficient estimate for *Post*Std. RH Earnings Surprise* being a valid measure of the use of earnings information by retail investors trading on Robinhood. It would be problematic if this coefficient estimate was significantly different than zero when retail investors are unable to trade on Robinhood. Therefore, I estimate my main specification (i.e., Columns 2 and 4 of Table 3) within the sample of stocks whose price crossed the +/- 5% push notification threshold during a Robinhood outage. The results are presented in Table 6. For both positive and negative push notification samples, the coefficient estimates for *Post*Std. RH Earnings Surprise* are statistically insignificant from zero. This placebo evidence supports the validity of my research design in isolating the effects of retail investor trading that occurs on Robinhood.

Overall, the results in Section 4.2 suggest that brokerages' content curation practices impact retail investors' use of earnings information to trade. This inference is supported by rich institutional details as well as additional analyses probing the validity of several aspects of my research design.

4.3 Robinhood's Digital Engagement Practices and Retail Investor Informativeness

My last analysis examines the 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:

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

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. *Post* 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.[19]

The results from estimating Equation 5 are presented in Table 7. 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. This estimated effect size is relatively small, and the overall statistical significance of these estimates is weak.

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[19] I allow control variable coefficients 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.

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, another interpretation relevant to the ongoing policy discussions is that retail investors are not *less informed* after a push notification. Considering the small positive effect following positive notifications and the null effect following negative notifications, my overall conclusion is that Robinhood's digital engagement practices do not seem to hinder aggregate retail investor informativeness.

5. Conclusion

In this paper, I examine whether digital engagement practices affect investor information processing and trading by focusing on two notable digital engagement practices: (i) push notifications and (ii) content curation. 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 Robinhood's content curation practices impact the information retail investors use to trade. Using an earnings surprise measure created to reflect the visual perception of earnings information displayed on Robinhood, 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 influence of these digital engagement practices does not have a meaningful impact—positive nor negative—on aggregate retail investor informativeness.

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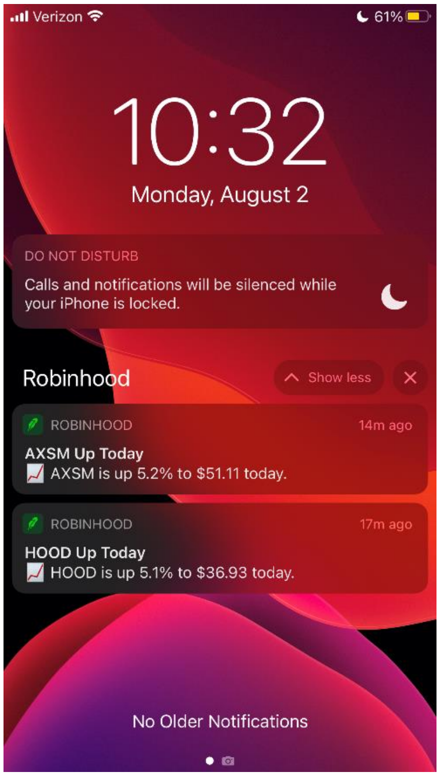
Figure 1: Example of Robinhood Push Notification

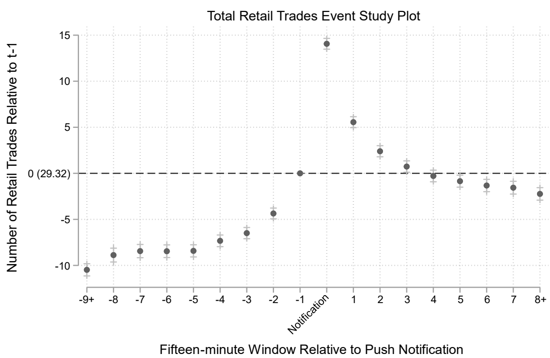


This figure shows an example of Robinhood's mobile push notifications.

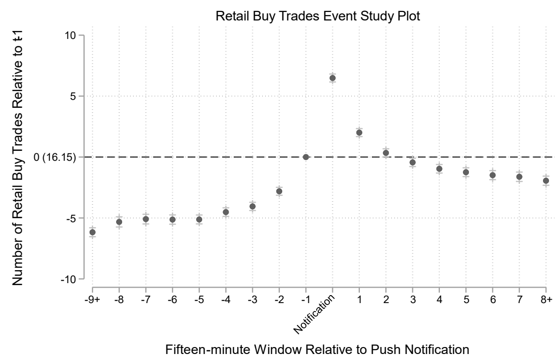
Figure 2: ***Retail Reaction*** Event Study Plots

Panel A: Positive 5% Push Notification Sample

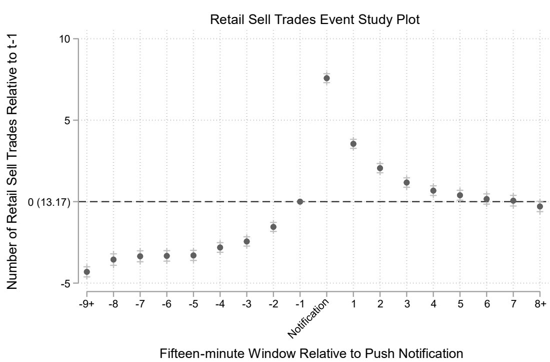
Total Retail Trades



Retail Buy Trades



Retail Sell Trades



Retail Order Imbalance

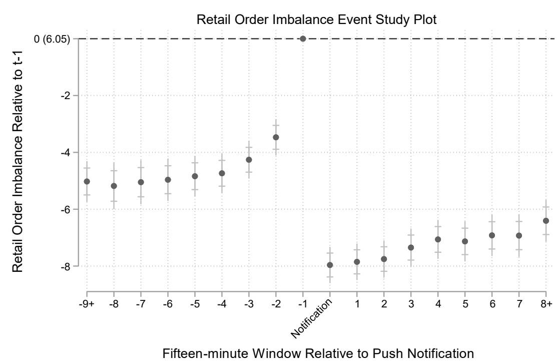


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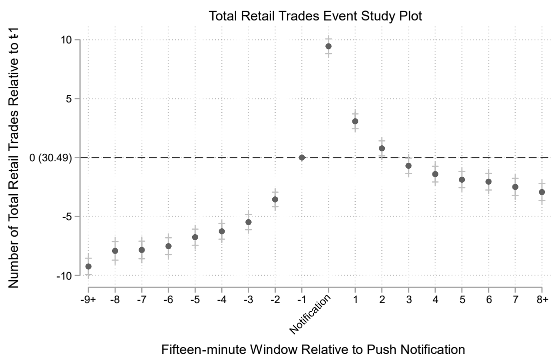
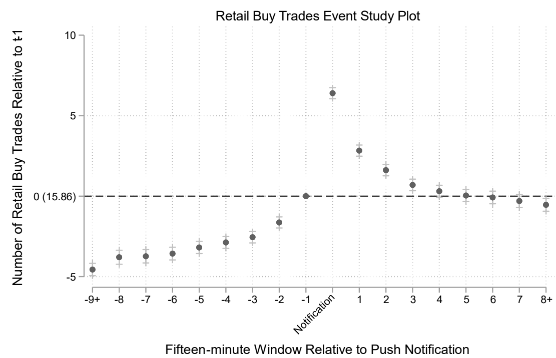
Figure 2: ***Retail Reaction*** Event Study Plots

Panel B: Negative 5% Push Notification Sample

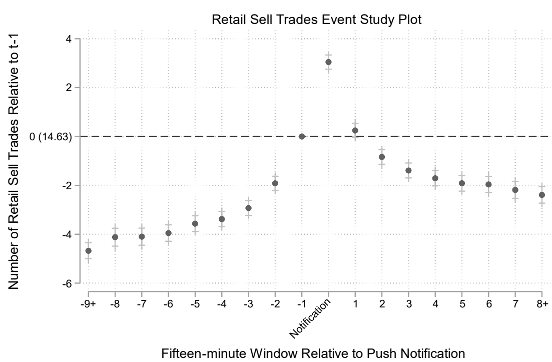
Total Retail Trades



Retail Buy Trades



Retail Sell Trades



Retail Order Imbalance

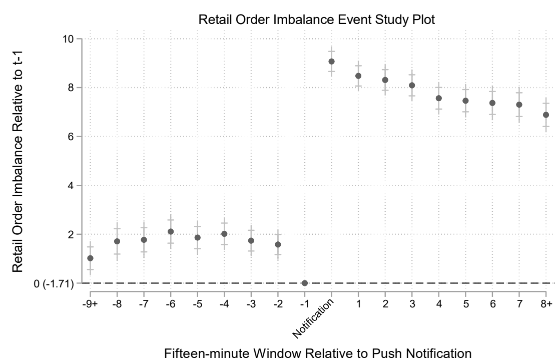
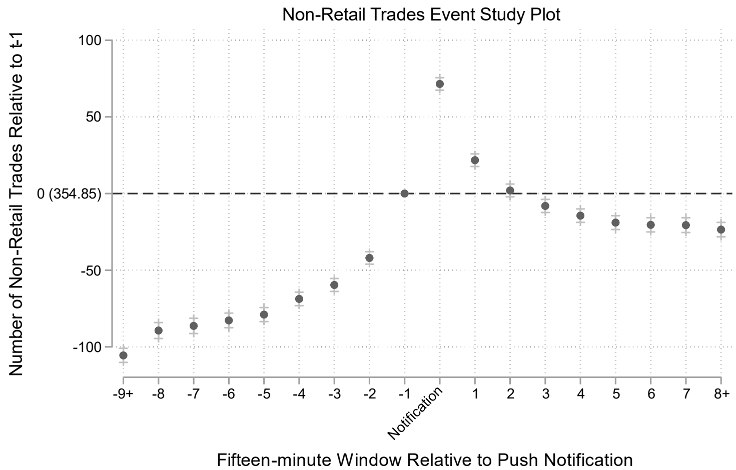


Figure 2 shows event study plots from estimating Equation 1. Panel A shows estimates for the positive five percent sample, and Panel B shows estimates for the negative five percent sample. The dependent variable is indicated above each plot. The event window t=0 (labeled "Notification" in the plots) 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. The light grey bars extending from the dots visualize the uncertainty of the coefficient estimates. The interval of these light grey bars within the horizontal dash marks represents the 95 percent pointwise confidence interval based on robust standard errors clustered by stock and date. The full interval of the light grey bar represents the 95 percent uniform confidence band (Olea and Plagborg-Moller, 2019). Both measures of estimate uncertainty are quite small and may not be viewable without zooming in.

Figure 3: *Total Non-Retail Trades* Event Study Plots

Panel A: Positive 5% Push Notifications Sample



Panel B: Negative 5% Push Notifications Sample

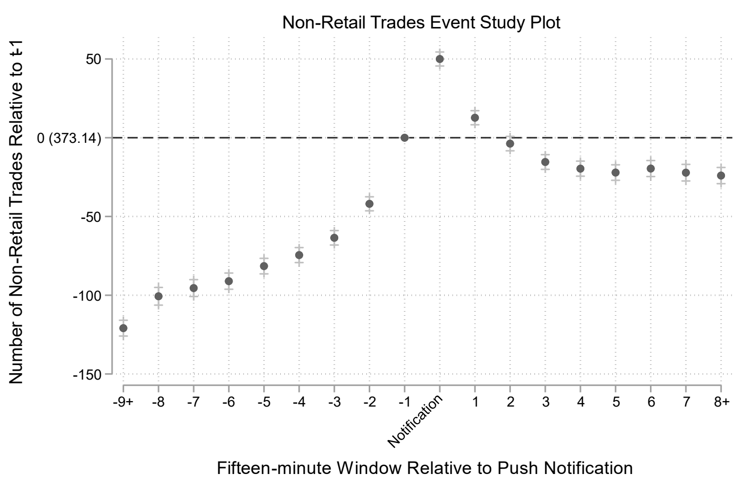
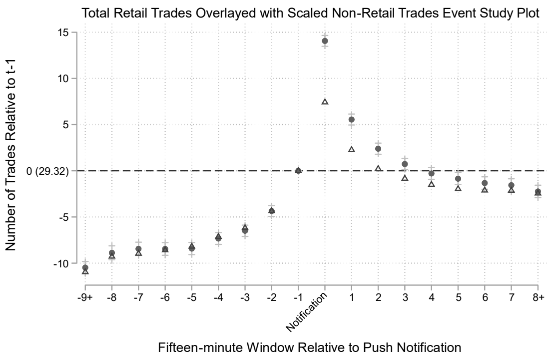


Figure 3 shows event study plots from estimating Equation 1 using *Total Non-Retail Trades* as the dependent variable. Panel A shows estimates for the positive five percent sample, and Panel B shows estimates for the negative five percent sample. The event window t=0 (labeled "Notification" in the plots) 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. The light grey bars extending from the dots visualize the uncertainty of the coefficient estimates. The interval of these light grey bars within the horizontal dash marks represents the 95 percent pointwise confidence interval based on robust standard errors clustered by stock and date. The full interval of the light grey bar represents the 95 percent uniform confidence band (Olea and Plagborg-Moller, 2019). Both measures of estimate uncertainty are quite small and may not be viewable without zooming in.

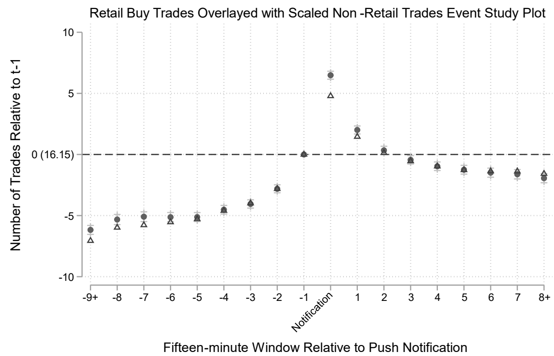
Figure 4: *Retail Reaction* Plots Overlayed with Scaled *Non-Retail Trades* Plots

Panel A: Positive 5% Push Notifications Sample

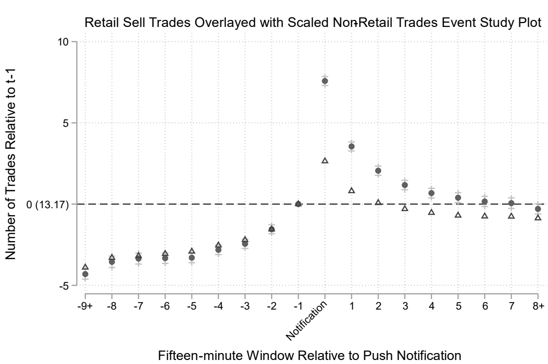
Total Retail Trades



Retail Buy Trades



Retail Sell Trades



Retail Order Imbalance

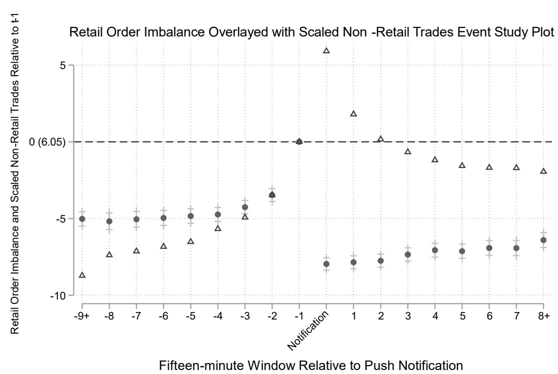


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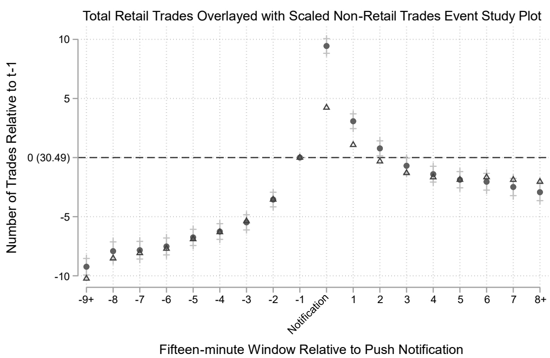
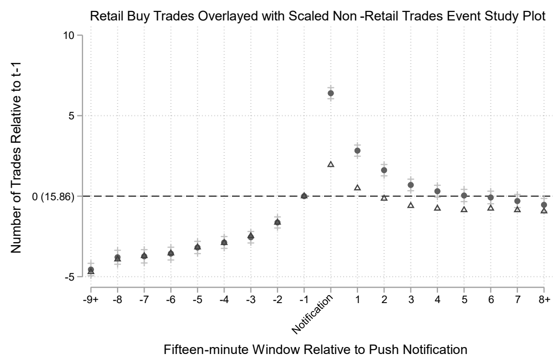
Figure 4: *Retail Reaction* Plots Overlayed with Scaled *Non-Retail Trades* Plots

Panel B: Negative 5% Push Notification Sample

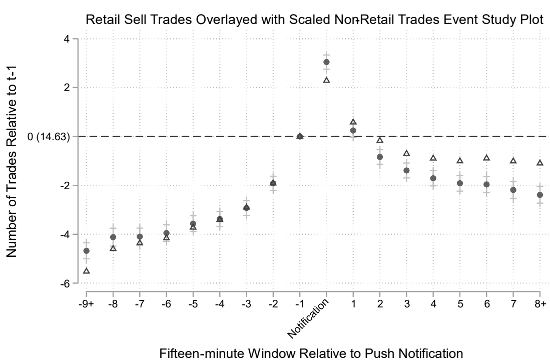
Total Retail Trades



Retail Buy Trades



Retail Sell Trades



Retail Order Imbalance

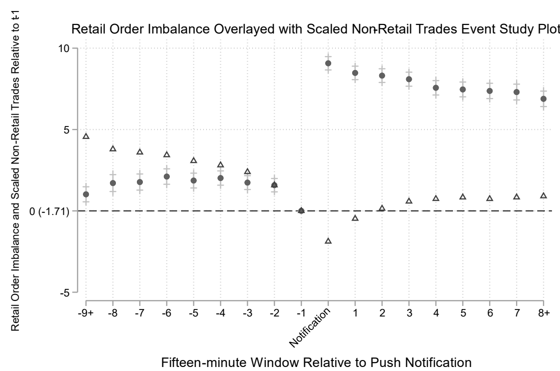
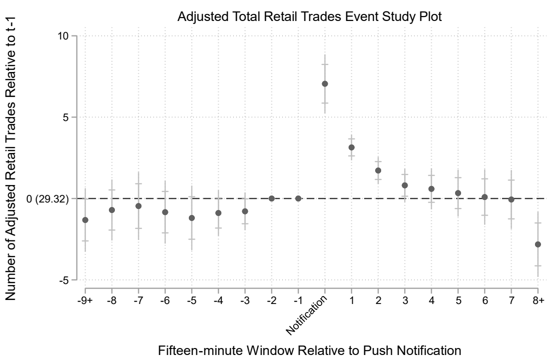


Figure 4 shows the event study plots from Figure 2 (i.e., *Retail Reaction* event study plots) as the dots with error bars overlayed with the scaled event study plots from Figure 3 (i.e., *Non-Retail Trades* event study plots) as the triangles. Panel A shows estimates for the positive five percent sample, and Panel B shows estimates for 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* (dots 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.

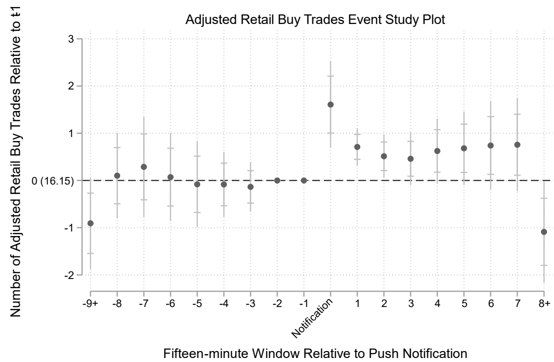
Figure 5: Adjusted *Retail Reaction* Event Study Plots

Panel A: Positive 5% Push Notification Sample

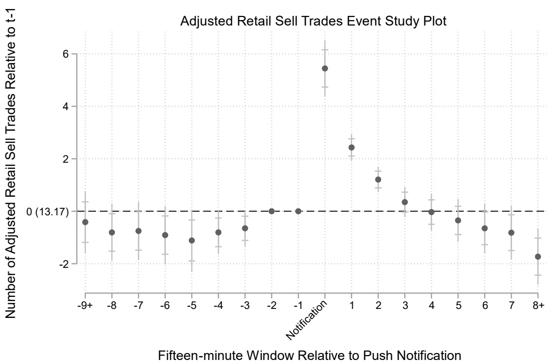
Total Retail Trades



Retail Buy Trades



Retail Sell Trades



Retail Order Imbalance

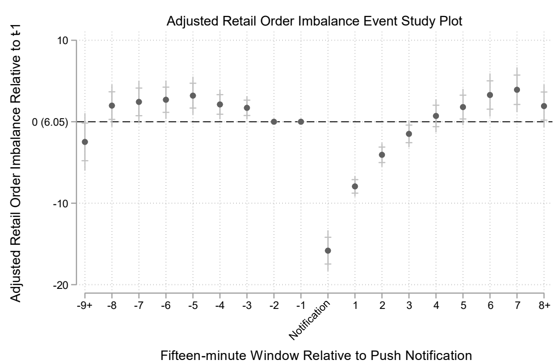


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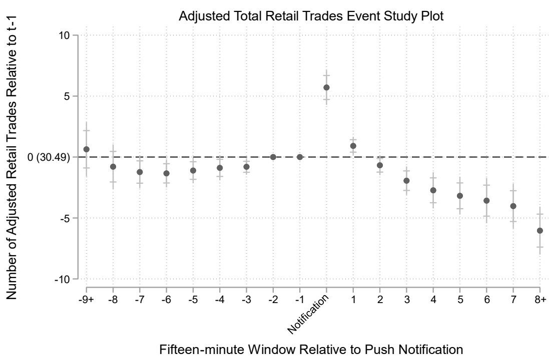
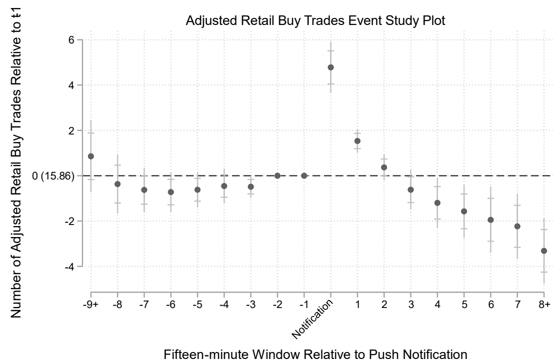
Figure 5: Adjusted *Retail Reaction* Event Study Plots

Panel B: Negative 5% Push Notification Sample

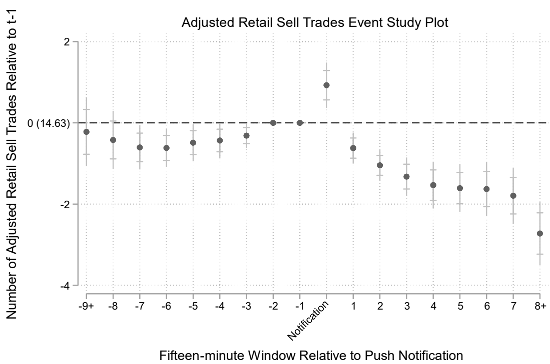
Total Retail Trades



Retail Buy Trades



Retail Sell Trades



Retail Order Imbalance

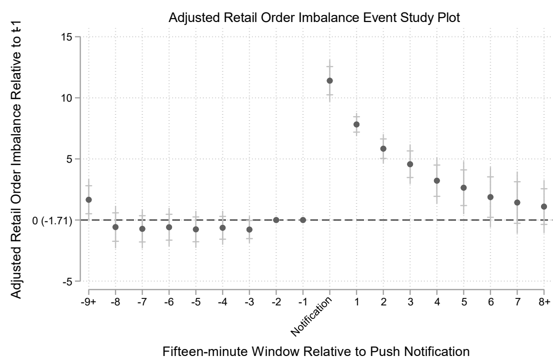
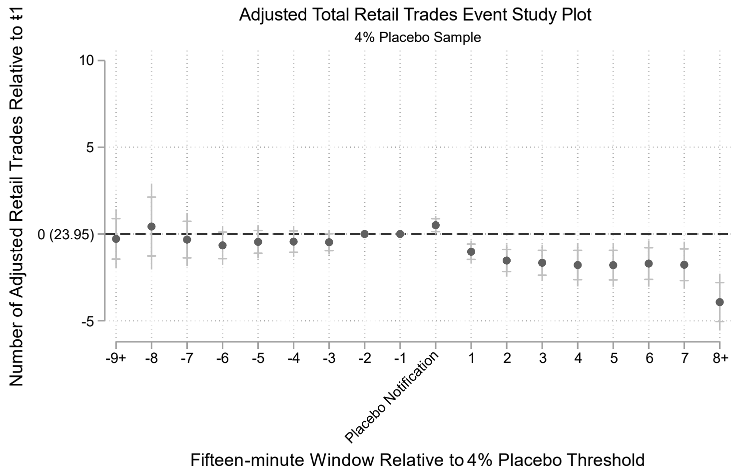


Figure 5 shows event study plots from using the two-stage least squares proxy variable approach developed in Freyaldenhoven et al. (2019). Panel A shows estimates for the positive five percent sample, and Panel B shows estimates for the negative five percent sample. The dependent variable is indicated 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 estimates at t-1 and t-2 are 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. The light grey bars extending from the dots visualize the uncertainty of the coefficient estimates. The interval of these light grey bars within the horizontal dash marks represents the 95 percent pointwise confidence interval based on robust standard errors clustered by stock and date. The full interval of the light grey bar represents the 95 percent uniform confidence band (Olea and Plagborg-Moller, 2019). Both measures of estimate uncertainty are quite small and may not be viewable without zooming in.

Figure 6: Adjusted *Total Retail Trades* Event Study Plots Using 4% Placebo Threshold

Panel A: Positive 4% Placebo Threshold Sample



Panel B: Negative 4% Placebo Threshold Sample

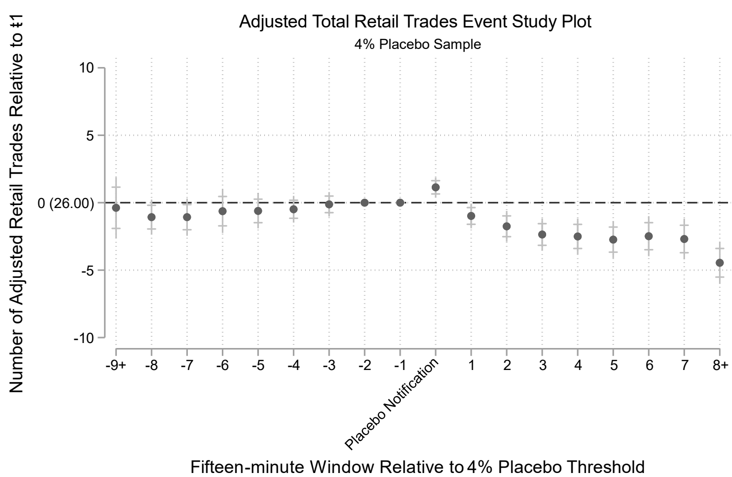
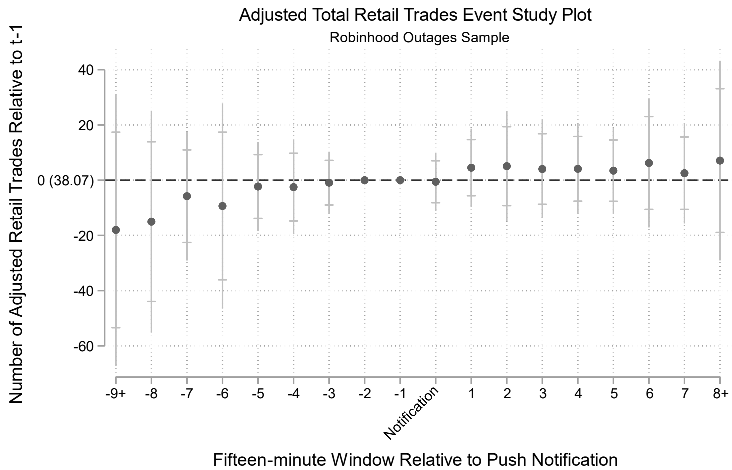


Figure 6 shows placebo event study plots from using the two-stage least squares proxy variable approach developed in Freyaldenhoven et al. (2019) on the sample of stocks whose price moved at least 4% but less than 5% intraday. The event window t=0 (labeled "Placebo Notification" in the plots) is the first fifteen-minute window after a stock's intraday movement reaches the 4% placebo threshold. The coefficient estimates at t-1 and t-2 are normalized to equal zero. The coefficient estimates on the remaining event windows measure the level of *Adjusted Total Retail Trades* 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 *Total Retail Trades* during the t-1 window next to the 'zero' reference line on the Y-axis. The light grey bars extending from the dots visualize the uncertainty of the coefficient estimates. The interval of these light grey bars within the horizontal dash marks represents the 95 percent pointwise confidence interval based on robust standard errors clustered by stock and date. The full interval of the light grey bar represents the 95 percent uniform confidence band (Olea and Plagborg-Moller, 2019).

Figure 7: Adjusted *Total Retail Trades* Event Study Plots During Robinhood Outages

Panel A: Positive 5% Push Notifications Sample During Robinhood Outages



Panel B: Negative 5% Push Notifications Sample During Robinhood Outages

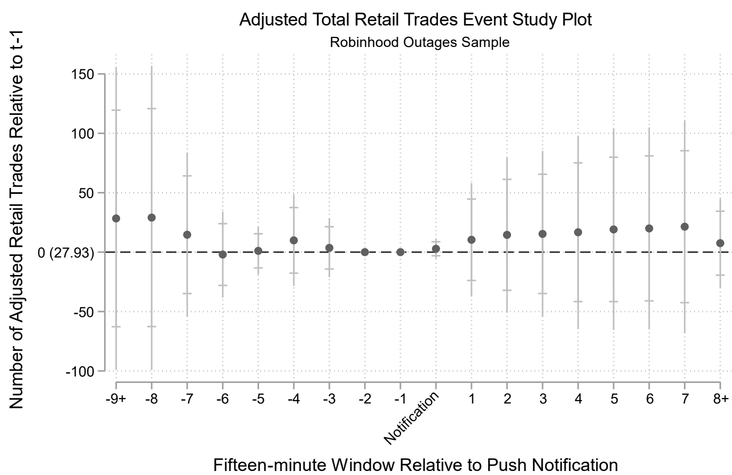
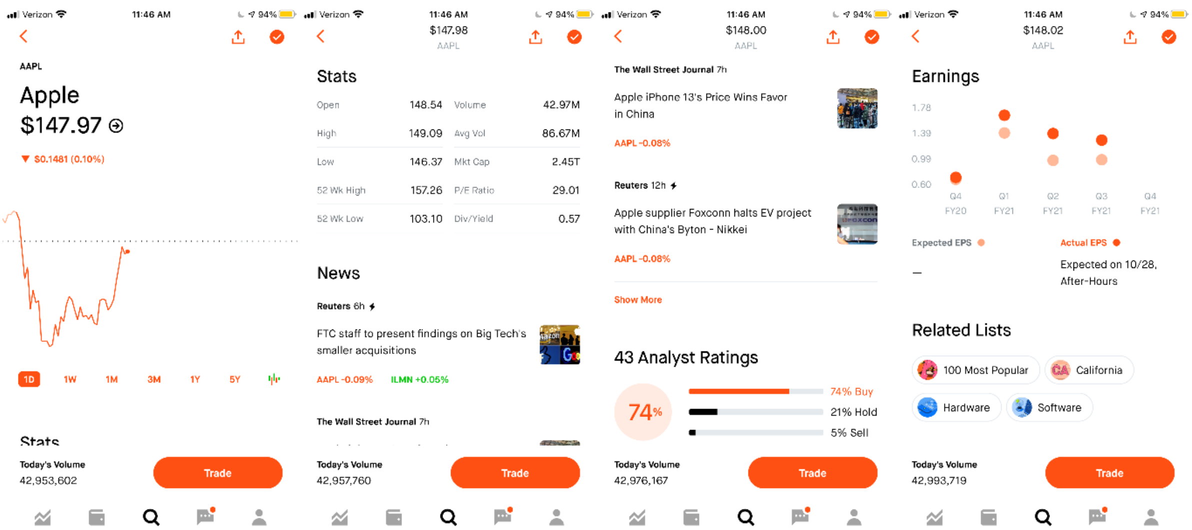


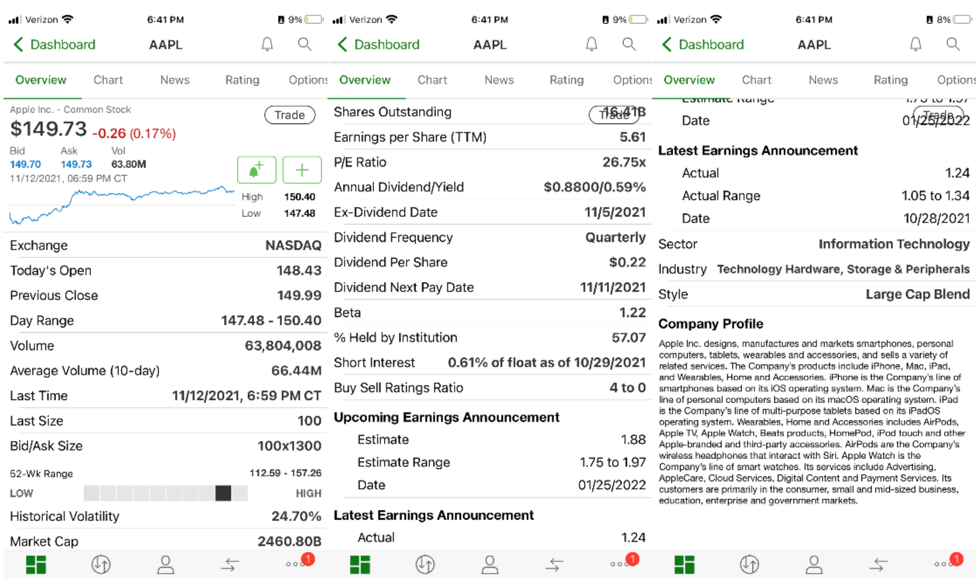
Figure 7 shows event study plots from using the two-stage least squares proxy variable approach developed in Freyaldenhoven et al. (2019) on the sample of firms whose intraday return reaches 5% during a Robinhood outage. Panel A shows estimates for the positive five percent sample, and Panel B shows estimates for the negative five percent sample. The event window t=0 (labeled "Notification" in the plots) is the first fifteen-minute window after a Robinhood push notification. The coefficient estimates at t-1 and t-2 are normalized to equal zero. The coefficient estimates on the remaining event windows measure the level of *Adjusted Total Retail Trades* 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 *Total Retail Trades* during the t-1 window next to the 'zero' reference line on the Y-axis. The light grey bars extending from the dots visualize the uncertainty of the coefficient estimates. The interval of these light grey bars within the horizontal dash marks represents the 95 percent pointwise confidence interval based on robust standard errors clustered by stock and date. The full interval of the light grey bar represents the 95 percent uniform confidence band (Olea and Plagborg-Moller, 2019).

Figure 8: Robinhood's Content Curation Practices

Panel A: Robinhood Platform

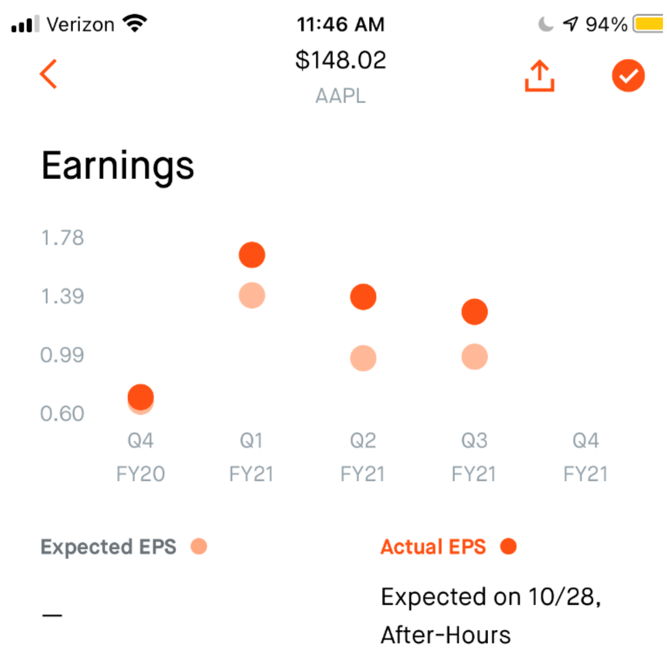


Panel B: TD Ameritrade Platform



This figure shows the user interface and content curation practices of the Robinhood mobile app (Panel A) and TD Ameritrade mobile app (Panel B).

Figure 9: Robinhood's Visual Display of Earnings Information



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 for the positive five percent sample, and Panel B presents descriptive statistics for the negative five percent sample.

Table 2: The Impact of Robinhood's Content Curation 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*
Post	-5.790***	-8.846***	-11.55***	-15.42***
	(-27.70)	(-23.16)	[0.496]	[0.623]
Post*Std. RH Earnings Surprise	0.344**	0.341**	0.707***	0.684***
	(2.103)	(2.067)	[0.236]	[0.237]
Post*Std. Return$_{t-5,t-1}$	0.124	0.021	-1.309***	-1.501***
	(0.766)	(0.133)	[0.390]	[0.388]
Post*Std. Return$_{t-63,t-1}$	-0.188	-0.306*	-1.180***	-1.392***
	(-0.977)	(-1.692)	[0.407]	[0.397]
Post*Std. Return$_{t-253,t-1}$	0.536***	0.531***	-0.155	-0.166
	(3.917)	(3.901)	[0.406]	[0.403]
Post*Std. Analyst Buy %	-0.697***	-0.700***	0.199	0.226
	(-3.313)	(-3.303)	[0.325]	[0.349]
Post*Std. Analyst Sell %	-0.083	-0.078	-0.529	-0.421
	(-0.473)	(-0.445)	[0.336]	[0.346]
Std. RH Earnings Surprise	-0.092		-0.101	
	(-0.684)		[0.155]	
Std. Return$_{t-5,t-1}$	0.558***		1.024	
	(2.850)		[0.623]	
Std. Return$_{t-63,t-1}$	0.522***		0.313	
	(3.205)		[0.825]	
Std. Return$_{t-253,t-1}$	0.533***		-11.59***	
	(3.350)		[4.146]	
Std. Analyst Buy %	1.777***		11.77***	
	(10.38)		[1.224]	
Std. Analyst Sell %	-0.027		-6.763**	
	(-0.167)		[2.819]	
Stock-Day Fixed Effects	-	Included	-	Included
Time of Day Fixed Effects	Included	Included	Included	Included
Adj. R^2	0.004	0.055	0.027	0.693
N	449,308	449,308	449,308	449,308

(Continued)

Table 2: The Impact of Robinhood's Content Curation 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*
Post	7.347***	9.373***	9.024***	11.41***
	(30.13)	(23.33)	[0.302]	[0.475]
Post*Std. RH Earnings Surprise	-0.571***	-0.578***	-0.600***	-0.579***
	(-3.319)	(-3.304)	[0.195]	[0.197]
Post*Std. $Return_{t-5,t-1}$	-0.121	0.0102	-0.510**	-0.367*
	(-0.655)	(0.0598)	[0.231]	[0.232]
Post*Std. $Return_{t-63,t-1}$	0.297	0.452**	0.437*	0.567***
	(1.333)	(2.377)	[0.240]	[0.200]
Post*Std. $Return_{t-253,t-1}$	-0.453***	-0.472***	-0.110	-0.019
	(-3.081)	(-3.167)	[0.309]	[0.308]
Post*Std. Analyst Buy %	1.083***	1.121***	0.729***	0.747***
	(4.781)	(4.949)	[0.241]	[0.258]
Post*Std. Analyst Sell %	0.527***	0.547***	0.489**	0.562***
	(2.695)	(2.820)	[0.207]	[0.210]
Std. RH Earnings Surprise	-0.139		0.113	
	(-0.955)		[0.151]	
Std. $Return_{t-5,t-1}$	-0.006		1.503***	
	(-0.026)		[0.509]	
Std. $Return_{t-63,t-1}$	-1.326***		-1.584***	
	(-6.022)		[0.536]	
Std. $Return_{t-253,t-1}$	-0.745***		5.862***	
	(-3.789)		[2.053]	
Std. Analyst Buy %	-1.108***		-5.359***	
	(-5.507)		[0.633]	
Std. Analyst Sell %	0.597***		3.624***	
	(2.998)		[1.335]	
Stock-Day Fixed Effects	-	Included	-	Included
Time of Day Fixed Effects	Included	Included	Included	Included
Adj. R^2	0.008	0.077	0.017	0.483
N	471,906	471,906	471,906	471,906

(Continued)

Table 2 (Continued)

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 for the positive five percent push notification sample, and Panel B presents the results for the negative five percent push notification 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 *Post*Std. RH Earnings Surprise*. I include controls for the non-earnings information available on Robinhood and interact these controls with *Post*. These control variables include *Std. Return*$_{t-5,t-1}$, *Std. Return*$_{t-63,t-1}$, *Std. Return*$_{t-253,t-1}$, *Std. Analyst Buy %*, and *Std. Analyst Sell %* as defined in Section 4. All the independent variables except for *Post* 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 in Columns 2 and 4. I include stock-day and time of day fixed effects as indicated but do not report the coefficients. Columns 1 and 2 report OLS coefficient estimates and (in parentheses) *t*-statistics based on robust standard errors clustered by stock and date. Columns 3 and 4 report OLS coefficient estimates and [in brackets] standard errors calculated using a bootstrap procedure where each of the 250 bootstrapped samples are drawn randomly with replacement. ***, **, 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*
Post	-5.791***	-8.847***	-11.55***	-15.42***
	(-27.70)	(-23.17)	[0.496]	[0.615]
Post*Std. RH Earnings Surprise	0.359**	0.359**	0.769***	0.746***
	(2.049)	(2.026)	[0.254]	[0.266]
Post*Std. Academic Earnings Surprise	-0.039	-0.0461	-0.168	-0.169
	(-0.181)	(-0.212)	[0.247]	[0.272]
Post*Std. $Return_{t-5,t-1}$	0.123	0.0201	-1.310***	-1.501***
	(0.761)	(0.129)	[0.390]	[0.411]
Post*Std. $Return_{t-63,t-1}$	-0.187	-0.305*	-1.178***	-1.390***
	(-0.972)	(-1.686)	[0.407]	[0.370]
Post*Std. $Return_{t-253,t-1}$	0.537***	0.532***	-0.154	-0.165
	(3.918)	(3.902)	[0.406]	[0.433]
Post*Std. Analyst Buy %	-0.697***	-0.700***	0.199	0.225
	(-3.313)	(-3.303)	[0.324]	[0.329]
Post*Std. Analyst Sell %	-0.084	-0.0789	-0.532	-0.424
	(-0.475)	(-0.448)	[0.336]	[0.333]
Std. RH Earnings Surprise	-0.071		-0.125	
	(-0.482)		[0.103]	
Std. Academic Earnings Surprise	-0.058		0.086	
	(-0.313)		[0.551]	
Std. $Return_{t-5,t-1}$	0.558***		1.023	
	(2.852)		[0.623]	
Std. $Return_{t-63,t-1}$	0.522***		0.312	
	(3.205)		[0.824]	
Std. $Return_{t-253,t-1}$	0.533***		-11.59***	
	(3.351)		[4.146]	
Std. Analyst Buy %	1.777***		11.77***	
	(10.38)		[1.224]	
Std. Analyst Sell %	-0.029		-6.762**	
	(-0.174)		[2.815]	
Stock-Day Fixed Effects	-	Included	-	Included
Time of Day Fixed Effects	Included	Included	Included	Included
Adj. R^2	0.004	0.055	0.027	0.693
N	449,304	449,304	449,304	449,304

(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*
Post	7.347***	9.373***	9.024***	11.41***
	(30.15)	(23.33)	[0.302]	[0.497]
Post*Std. RH Earnings Surprise	-0.493***	-0.492***	-0.526**	-0.497**
	(-2.724)	(-2.669)	[0.207]	[0.211]
Post*Std. Academic Earnings Surprise	-0.218	-0.240	-0.208	-0.227
	(-0.923)	(-1.007)	[0.240]	[0.241]
Post*Std. $Return_{t-5,t-1}$	-0.119	0.0123	-0.508**	-0.365*
	(-0.644)	(0.0723)	[0.231]	[0.240]
Post*Std. $Return_{t-63,t-1}$	0.298	0.453**	0.438*	0.568***
	(1.338)	(2.385)	[0.240]	[0.219]
Post*Std. $Return_{t-253,t-1}$	-0.451***	-0.469***	-0.108	-0.0168
	(-3.066)	(-3.151)	[0.309]	[0.290]
Post*Std. Analyst Buy %	1.082***	1.120***	0.728***	0.746***
	(4.778)	(4.946)	[0.241]	[0.257]
Post*Std. Analyst Sell %	0.524***	0.543***	0.486**	0.559***
	(2.680)	(2.804)	[0.207]	[0.212]
Std. RH Earnings Surprise	-0.246		0.094	
	(-1.620)		[0.106]	
Std. Academic Earnings Surprise	0.297*		0.208	
	(1.752)		[0.321]	
Std. $Return_{t-5,t-1}$	-0.009		1.501***	
	(-0.038)		[0.510]	
Std. $Return_{t-63,t-1}$	-1.327***		-1.585***	
	(-6.027)		[0.536]	
Std. $Return_{t-253,t-1}$	-0.749***		5.859***	
	(-3.805)		[2.054]	
Std. Analyst Buy %	-1.107***		-5.358***	
	(-5.503)		[0.633]	
Std. Analyst Sell %	0.602***		3.627***	
	(3.029)		[1.333]	
Stock-Day Fixed Effects	-	Included	-	Included
Time of Day Fixed Effects	Included	Included	Included	Included
Adj. R^2	0.008	0.077	0.017	0.483
N	471,906	471,906	471,906	471,906

(Continued)

Table 3 (Continued)

This table presents the results from estimating Equation 4 using OLS regression with both the Robinhood and academic measures of earnings surprise included. Panel A presents the results for the positive five percent push notification sample, and Panel B presents the results for the negative five percent push notification 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 *Post*Std. RH Earnings Surprise* and *Post*Std. Academic Earnings Surprise*. I include controls for the non-earnings information available on Robinhood and interact these controls with *Post*. These control variables include *Std.* $Return_{t-5,t-1}$, *Std.* $Return_{t-63,t-1}$, *Std.* $Return_{t-253,t-1}$, *Std. Analyst Buy %*, and *Std. Analyst Sell %* as defined in Section 4. All the independent variables except for *Post* 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 in Columns 2 and 4. I include stock-day and time of day fixed effects as indicated but do not report the coefficients. Columns 1 and 2 report OLS coefficient estimates and (in parentheses) *t*-statistics based on robust standard errors clustered by stock and date. Columns 3 and 4 report OLS coefficient estimates and [in brackets] standard errors calculated using a bootstrap procedure where each of the 250 bootstrapped samples are drawn randomly with replacement. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% p-levels (two-tailed), respectively.

Table 4: Examining the Use of Earnings Information Across Earnings Staleness Subsamples

Panel A: Positive 5% Push Notification Sample

Dependent variable:	*(1)* *Retail Order Imbalance*	*(2)* *Retail Order Imbalance*	*(3)* *Retail Order Imbalance*	*(4)* *Adjusted Retail Order Imbalance*	*(5)* *Adjusted Retail Order Imbalance*	*(6)* *Adjusted Retail Order Imbalance*
Post	-8.750***	-8.478***	-9.395***	-14.98***	-14.52***	-17.34***
	(-13.90)	(-14.56)	(-12.84)	[0.819]	[0.805]	[1.127]
Post*Std. RH	-0.234	0.940***	0.547*	0.168	1.236***	0.997**
Earnings Surprise	(-0.783)	(3.045)	(1.696)	[0.436]	[0.380]	[0.473]
Post*Std. Academic	0.549	-0.593	0.118	0.461	-0.707	-0.068
Earnings Surprise	(1.578)	(-1.600)	(0.338)	[0.386]	[0.433]	[0.438]
# of Days Since EA Subsample	[1, 30]	[31, 60]	[61, 100]	[1, 30]	[31, 60]	[61, 100]
Post*Control Variables	Included	Included	Included	Included	Included	Included
Stock-Day Fixed Effects	Included	Included	Included	Included	Included	Included
Time of Day Fixed Effects	Included	Included	Included	Included	Included	Included
Adj. R^2	0.056	0.056	0.053	0.694	0.747	0.633
N	153,212	149,732	124,488	151,994	148,572	123,431

(Continued)

Table 4: Examining the Use of Earnings Information Across Earnings Staleness Subsamples

Panel B: Negative 5% Push Notification Sample

Dependent variable:	(1) *Retail Order Imbalance*	(2) *Retail Order Imbalance*	(3) *Retail Order Imbalance*	(4) *Adjusted Retail Order Imbalance*	(5) *Adjusted Retail Order Imbalance*	(6) *Adjusted Retail Order Imbalance*
Post	9.089***	8.924***	9.754***	11.15***	11.13***	11.73***
	(13.53)	(14.45)	(13.90)	[0.726]	[0.693]	[0.788]
Post*Std. RH	-0.498*	-0.305	-0.602*	-0.412	-0.310	-0.772*
Earnings Surprise	(-1.743)	(-0.975)	(-1.705)	[0.329]	[0.373]	[0.399]
Post*Std. Academic	0.176	-0.410	-0.371	0.079	-0.381	-0.313
Earnings Surprise	(0.472)	(-1.184)	(-0.983)	[0.384]	[0.365]	[0.368]
# of Days Since EA Subsample	[1, 30]	[31, 60]	[61, 100]	[1, 30]	[31, 60]	[61, 100]
Post*Control Variables	Included	Included	Included	Included	Included	Included
Stock-Day Fixed Effects	Included	Included	Included	Included	Included	Included
Time of Day Fixed Effects	Included	Included	Included	Included	Included	Included
Adj. R^2	0.079	0.077	0.078	0.427	0.543	0.474
N	164,276	153,660	128,408	162,962	152,234	127,366

This table presents the results from estimating the specifications in Columns 2 and 4 of Table 3 partitioned by the number of days since the firm's most recent earnings announcement. Panel A presents the results for the positive five percent push notification sample, and Panel B presents the results for the negative five percent push notification 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 *Post*Std. RH Earnings Surprise* and *Post*Std. Academic Earnings Surprise*. Columns 1 and 4 include push notifications that occurred between one and thirty days after a firm's earnings announcement. Columns 2 and 5 include push notifications that occurred between thirty-one and sixty days after a firm's earnings announcement. Columns 3 and 6 include push notifications that occurred between sixty-one and one-hundred days after a firm's earnings announcement. All the independent variables except for *Post* are standardized to have a mean equal to zero and standard deviation equal to one. I include control variables, stock-day fixed effects, and time of day fixed effects as indicated but do not report the coefficients. Columns 1-3 report OLS coefficient estimates and (in parentheses) *t*-statistics based on robust standard errors clustered by stock and date. Columns 4-6 report OLS coefficient estimates and [in brackets] standard errors calculated using a bootstrap procedure where each of the 250 bootstrapped samples are drawn randomly with replacement. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% p-levels (two-tailed), respectively.

Table 5: Difference-in-Differences Analysis Around the Introduction of Earnings Information on Robinhood

Panel A: Positive 5% Push Notification Sample

Dependent variable:	*(1)* *Retail Order Imbalance*	*(2)* *Adjusted Retail Order Imbalance*
Post Notification	-22.07***	-28.31***
	(-4.972)	[5.622]
Post Notification*Std. RH Earnings Surprise	1.162	1.530
	(0.525)	[3.854]
Post Notification*Std. Academic Earnings Surprise	2.954	2.226
	(1.517)	[2.066]
Post Notification*Post Earnings Introduction	1.135	8.024*
	(0.280)	[4.706]
Post Notification*Post Earnings Introduction*Std. RH Earnings Surprise	2.470**	2.894*
	(2.18)	[1.523]
Post Notification*Post Earnings Introduction*Std. Academic Earnings Surprise	-2.727	-0.670
	(-0.992)	[3.080]
Controls	Absorbed	Absorbed
Post Notification*Controls	Included	Included
Post Earnings Info*Controls	Absorbed	Absorbed
Post Notification*Post Earnings Info*Controls	Included	Included
Stock-Day Fixed Effects	Included	Included
Time of Day Fixed Effects	Included	Included
Adj. R^2	0.082	0.510
N	3,468	3,440

(Continued)

Table 5: Difference-in-Differences Analysis Around the Introduction of Earnings Information on Robinhood

Panel B: Negative 5% Push Notification Sample

Dependent variable:	*(1)* *Retail Order Imbalance*	*(2)* *Adjusted Retail Order Imbalance*
Post Notification	8.773**	10.08**
	(1.996)	[4.630]
Post Notification*Std. RH Earnings Surprise	-1.188	-2.474
	(-0.439)	[2.830]
Post Notification*Std. Academic Earnings Surprise	0.246	0.355
	(0.107)	[2.316]
Post Notification*Post Earnings Introduction	0.415	4.376
	(0.104)	[5.069]
Post Notification*Post Earnings Introduction*Std. RH Earnings Surprise	-2.741*	-2.433*
	(-1.712)	[1.440]
Post Notification*Post Earnings Introduction*Std. Academic Earnings Surprise	0.786	1.651
	(0.292)	[2.962]
Controls	Absorbed	Absorbed
Post Notification*Controls	Included	Included
Post Earnings Info*Controls	Absorbed	Absorbed
Post Notification*Post Earnings Info*Controls	Included	Included
Stock-Day Fixed Effects	Included	Included
Time of Day Fixed Effects	Included	Included
Adj. R^2	0.074	0.343
N	3,788	3,759

This table presents the results from augmenting the specifications in Columns 2 and 4 of Table 3 to run a difference-in-differences analysis around the January 17, 2017, introduction of earnings information on Robinhood. The sample period is limited to January 2017. Panel A presents the results for the positive five percent push notification sample, and Panel B presents the results for the negative five percent push notification sample. The dependent variable is either *Retail Order Imbalance* or *Adjusted Retail Order Imbalance* as defined in Section 4. *Post Notification* represents the post push notification indicator variable defined in Section 4.2. *Post Earnings Introduction* is an indicator variable equal to one for dates after January 17, 2017, and equal to zero otherwise. The primary coefficient estimates of interest are the interaction terms *Post Notification*Post Earnings Introduction*Std. RH Earnings Surprise* and *Post Notification*Post Earnings Introduction*Std. Academic Earnings Surprise*. All the independent variables except for *Post Notification* and *Post Earnings Introduction* are standardized to have a mean equal to zero and standard deviation equal to one. I include *Controls* and its full interactions with both post variables as indicated. Certain main effects and interaction terms 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. Column 1 reports OLS coefficient estimates and (in parentheses) *t*-statistics based on robust standard errors clustered by stock and date. Column 2 reports OLS coefficient estimates and [in brackets] standard errors calculated using a bootstrap procedure where each of the 250 bootstrapped samples are drawn randomly with replacement. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% p-levels (two-tailed), respectively.

Table 6: Placebo Analysis Examining Earnings Information Use During Robinhood Outages

Panel A: Positive 5% Push Notification Sample During Robinhood Outages

Dependent variable:	(1) *Retail Order Imbalance*	(2) *Adjusted Retail Order Imbalance*
Post	-2.318	-3.483
	(-1.260)	[2.592]
Post*Std. RH Earnings Surprise	-0.867	0.510
	(-0.523)	[1.846]
Post*Std. Academic Earnings Surprise	1.213	0.847
	(0.671)	[1.833]
Post Notification*Controls	Included	Included
Stock-Day Fixed Effects	Included	Included
Time of Day Fixed Effects	Included	Included
Adj. R^2	0.025	0.848
N	5,332	5,304

Panel B: Negative 5% Push Notification Sample During Robinhood Outages

Dependent variable:	(1) *Retail Order Imbalance*	(2) *Adjusted Retail Order Imbalance*
Post	2.873	2.944
	(1.199)	[2.063]
Post*Std. RH Earnings Surprise	2.316	1.437
	(1.270)	[1.955]
Post*Std. Academic Earnings Surprise	1.244	1.618
	(0.595)	[2.126]
Post Notification*Controls	Included	Included
Stock-Day Fixed Effects	Included	Included
Time of Day Fixed Effects	Included	Included
Adj. R^2	0.070	0.572
N	4,584	4,567

This table presents the results from estimating the specifications in Columns 2 and 4 of Table 3 for the sample of firms whose intraday return reaches +/- 5% during a Robinhood outage. Panel A presents the results for the positive five percent push notification sample, and Panel B presents the results for the negative five percent push notification 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 *Post*Std. RH Earnings Surprise* and *Post*Std. Academic Earnings Surprise*. I identify Robinhood outages using data from downdetector.com. All the independent variables except for *Post* are standardized to have a mean equal to zero and standard deviation equal to one. I include control variables, stock-day fixed effects, and time of day fixed effects as indicated but do not report the coefficients. Column 1 reports OLS coefficient estimates and (in parentheses) *t*-statistics based on robust standard errors clustered by stock and date. Column 2 reports OLS coefficient estimates and [in brackets] standard errors calculated using a bootstrap procedure where each of the 250 bootstrapped samples are drawn randomly with replacement. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% p-levels (two-tailed), respectively.

Table 7: 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)*
Post	0.028	0.017	0.017	0.007
	(0.672)	(0.469)	[0.045]	[0.039]
Post*Std. Retail Order Imbalance	0.065*	0.067*		
	(1.714)	(1.753)		
Post*Std. Adjusted Retail Order Imbalance			0.045*	0.052**
			[0.024]	[0.024]
Std. Retail Order Imbalance	-0.044	Monthly		Monthly
	(-1.493)			
Std. Adjusted Retail Order Imbalance			-0.144***	
			[0.041]	
Return$_{t-5,t-1}$	-4.203***	Monthly	-4.219***	Monthly
	(-2.887)		[1.618]	
Return$_{t-63,t-1}$	0.035	Monthly	0.020	Monthly
	(0.141)		[0.258]	
Return$_{t-253,t-1}$	-0.012	Monthly	-0.014	Monthly
	(-0.170)		[0.072]	
lnMVE	-0.132***	Monthly	-0.158***	Monthly
	(-2.610)		[0.057]	
lnMB	0.021	Monthly	0.025	Monthly
	(0.209)		[0.103]	
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
Adj. R^2	0.008	0.022	0.008	0.023
N	527,934	527,934	527,934	527,934

(Continued)

Table 7: 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)*
Post	-0.009	-0.007	-0.009	-0.009
	(-0.312)	(-0.253)	[0.029]	[0.027]
Post*Std. Retail Order Imbalance	-0.002	-0.005		
	(-0.056)	(-0.147)		
Post*Std. Adjusted Retail Order Imbalance			0.014	0.015
			[0.030]	[0.028]
Std. Retail Order Imbalance	0.023	Monthly		Monthly
	(0.772)			
Std. Adjusted Retail Order Imbalance			0.017	
			[0.037]	
Return$_{t-5,t-1}$	-3.956***	Monthly	-3.960***	Monthly
	(-3.916)		[1.053]	
Return$_{t-63,t-1}$	-0.171	Monthly	-0.173	Monthly
	(-1.010)		[0.182]	
Return$_{t-253,t-1}$	-0.065	Monthly	-0.066	Monthly
	(-0.995)		[0.068]	
lnMVE	0.027	Monthly	0.024	Monthly
	(0.688)		[0.044]	
lnMB	0.234***	Monthly	0.234**	Monthly
	(2.710)		[0.094]	
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
Adj. 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. The dependent variable is *Market-adjusted Return$_{t+1,t+5}$* as defined in Section 4.3. The primary coefficient estimates of interest are the interaction terms *Post*Std. Retail Order Imbalance* and *Post*Std. Adjusted Retail Order Imbalance*. I include *Return$_{t-5,t-1}$*, *Return$_{t-63,t-1}$*, *Return$_{t-253,t-1}$*, *lnMVE*, and *lnMB* as control variables (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. I allow the coefficient on the independent variables to vary each month as indicated. I include year-month and time of day fixed effects as indicated but do not report the coefficients. Columns 1 and 2 report OLS coefficient estimates and (in parentheses) *t*-statistics based on robust standard errors clustered by stock and date. Columns 3 and 4 report OLS coefficient estimates and [in brackets] standard errors calculated using a bootstrap procedure where each of the 250 bootstrapped samples are drawn randomly with replacement. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% p-levels (two-tailed), respectively.