Fast-Thinking Attention and the Disposition Effect

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Abstract: The disposition effect is the tendency of investors to sell stocks that have recently increased in value and hold stocks that have recently decreased in value. Although some evidence suggests that investor attention mitigates the disposition effect, this study finds that a certain type of attention—fast-thinking or "System 1" (Kahneman 2011) attention—has the opposite effect. I examine the disposition effect in investors who are presented with push notifications from the Robinhood brokerage, which I contend generates fast-thinking attention, and find that these notifications exacerbate the disposition effect. My results suggest that fast-thinking attention is detrimental to investors.

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1. Introduction

Investor attention is fundamental to how investors interact with financial markets. One strand of research demonstrates that greater investor attention leads to improvements in well-being or less biased decisions (e.g., Gargano and Rossi 2018; Dierick, Heyman, Inghelbrecht, and Stieperaere 2019). At the same time, investor attention has been linked to worse or riskier decisions such as chasing past returns or increased use of leverage (e.g., Barber, Huang, Odean, and Schwarz 2021; Arnold, Pelster, and Subramanyam 2021). In this paper I offer a partial resolution of this disconnect by distinguishing between two types of attention. I focus my paper on one type of attention—fast-thinking attention, or the "System 1" of Kahneman (2011)—and a common behavioral bias called the disposition effect. More specifically I examine whether fast-thinking attention mitigates or exacerbates the disposition effect in retail traders.

Kahneman (2011) provides a framework for two types of attention—fast-thinking (System 1) and slow-thinking (System 2). Fast thinking operates automatically and quickly and is best thought of as our intuition. Slow thinking, on the other hand, operates with more effort and includes mentally strenuous tasks like complex computations. Since slow thinking requires effort and strain, humans defer decision-making to their fast-thinking attention when possible. But fast-thinking attention is prone to biases such as loss aversion, narrow framing, and the sunk cost fallacy, which could lead investors to trade in line with the disposition effect. Given these differences I predict that fast-thinking attention exacerbates the disposition effect in retail investors.

I study the disposition effect because it is a consistent and robust behavioral bias individual investors display (Shefrin and Statman 1985; Barber and Odean 2013). Investors trading in line with this bias prefer to sell their winning investments and hold their losing investments. As Kahneman (2011) notes, the disposition effect is an instance of narrow framing. If investors must sell a stock, they should sell the stock they expect to do most poorly in the future. The reference point of the previous day's closing price or purchase price is irrelevant to a rational investor. The disposition effect is considered suboptimal because selling your winners both increases your tax bill and because stocks carry momentum (Shefrin and Statman 1985; Jagadeesh and Titman 1993). Taken together the literature suggests that the rational trader will trade opposite of the disposition effect (e.g., Barber and Odean 2013; Kahneman 2011).

In this study I use the brokerage Robinhood's push notifications (smartphone application pop-up messages) as a proxy for increased investor fast-thinking attention to an individual stock. One of the largest retail brokers in the U.S., Robinhood sends standard push notifications to its customers when a stock's price changes by 5% from the previous day's closing price. There are two main benefits of this setting for studying my research question. First, the alerts provide the investors an explicit narrow frame (current price in reference to yesterday's closing price) necessary for studying the disposition effect. Second, smartphone push notifications are often cited as being developed to increase users' attention by using behavioral cues—often backed by research on psychological fast-thinking biases (Hartmans 2022). Robinhood, like many application ("app") developers, has designed their app with their users' fast-thinking attention in mind, creating an interface that is easy to understand but does not have complex information that calls for slow thinking (Ingram 2019).

I construct my sample covering 2018-2020 starting with data from Robintrack which aggregates Robinhood ownership levels of stocks during that period. I collect all stock-days that cross an absolute 5% daily price change, triggering Robinhood's app to send a push notification to owners of the stock. Since the disposition effect explains when stocks are sold, I measure the change in the number of retail sale trades in the stock (following the Boehmer et al. 2021 algorithm) from the hour before the 5% trigger to the hour after the 5% trigger. A larger increase in the number of retail sale trades is consistent with more retail investors selling the stock after the price change. Using this sample I first examine whether there is evidence of the disposition effect, on average. I find that retail investors make more sale trades after a positive 5% price change compared to a negative 5% price change, consistent with investors selling daily winners more than daily losers. This preliminary result supports the notion that retail investors trade in line with the disposition effect when the stock's price is framed in reference to the previous day's closing price.

Next, I test my hypothesis by classifying firms into those with high or low fast-thinking attention following a 5% price change. To do so, I use the Robintrack data to classify stocks with high and low levels of Robinhood ownership. In other words, for stocks with a high level of Robinhood ownership, its investors receive more push notifications following a 5% price change. Its investors therefore will be paying more fast-thinking attention to the stock. Ideally, I would construct a sample of high and low Robinhood stocks and hold constant the total level of retail ownership in the stock. This way, I attribute any differences in retail selling activity to Robinhood's push notifications and not the inherent differences in retail ownership (i.e., differences in the ability for retail traders to sell the stock). To achieve equal retail ownership between the high and low Robinhood stocks, I entropy balance (Hainmueller 2012) the sample on the average retail trading volume in the past six months (and other variables). After holding constant the level of past retail trading activity, I assume that high and low Robinhood stocks have equal levels of retail ownership. This approach is designed to attribute any differences in selling activity to Robinhood traders reacting to push notifications.

I finally shift my attention to how fast-thinking attention (high Robinhood ownership after a 5% price change) affects the documented disposition effect. I show that stocks with high

Robinhood ownership have a higher increase in aggregate selling activity after a positive 5% price change—and no significant difference in aggregate selling activity after a negative 5% price change—compared to stocks with low Robinhood ownership. This evidence is consistent with fast-thinking attention increasing investors' tendency to sell winners and hold onto losers.

I conduct several additional analyses to ensure the robustness of my results to research design choices or endogeneity concerns. First, I find that investors trade less in line with the disposition effect in the second hour after the push notification when Robinhood investors' fast thinking has likely dissipated. I also document the robustness of my results to controlling for several determinants of retail trading activity. My results are robust to removing extreme continuation returns (Barber et al. 2021), controlling for the speed that the stock jumps or falls to cross the 5% threshold, and controlling for the COVID lockdown period which saw a boom in retail trading activity (Ozik et al. 2021). In additional analyses, I show that positive daily 5% stocks continue to achieve positive buy-and-hold abnormal returns for up to four months after the push notification trigger day, suggesting a negative welfare effect for retail investors who sell the daily winners.

Lastly, there may still be concerns about high and low Robinhood firms being inherently different in unobservable ways, so I provide an alternative identification technique for high and low fast-thinking attention. In this approach, I compare a period before Robinhood started sending notifications to after using firm fixed effects to control for any time-invariant firm characteristics associated with retail trading activity. This alternative setting offers a complementary identification technique to the entropy balancing approach used in my main analysis, bolstering the robustness of these results. Using this sample, I continue to find evidence consistent with fast-thinking attention exacerbating the disposition effect in retail investors.

This paper adds to three streams of literature. First, I contribute to the disposition effect literature. Although there is still some disagreement as to why the disposition effect exists (e.g., Heimer 2016; Kaustia 2010; Kahneman 2011), I provide evidence that supports narrow framing as at least a partial explanation by showing that retail investors trade in line with the disposition effect when brokers frame the stocks' price in reference to the previous day's closing price. To date researchers have documented the disposition effect with respect to the purchase price (see Barber and Odean 2013 or Kaustia 2010 for a review). The findings of my study are relevant because most brokerages and news sites display stocks' daily price movements most prominently. Additionally, research on the disposition effect is largely limited to a few datasets of individual investors who are mostly middle-aged men (e.g., Odean 1998; Kaustia 2010; Barber and Odean 2001; Dierick et al. 2019). My study uses a broad market-wide measure of retail trading activity to supplement these findings and show that retail investors on average trade in line with the disposition effect. I further contribute to the literature by showing that fast-thinking attention exacerbates this behavioral bias. Relatedly, Dierick et al. (2019) study investor logins to online brokerage accounts, finding that investors who log into their accounts (and stay logged in) more often trade less in line with the disposition effect. My results differ from those in Dierick et al. (2019), because most investor logins are likely not prompted by an external trigger, and therefore their measure of attention more likely captures slow-thinking attention.

Second, and more broadly, I contribute to the literature on investor attention in capital markets. This stream of literature studies what investors pay attention to—such as information confirming their prior beliefs (Cookson, Engelberg, and Mullins 2022), stocks that have high absolute returns (e.g., Barber et al. 2021; Berkman, Koch, Tuttle, and Zhang 2012), and more widely disseminated information (e.g., Blankespoor, Miller, and White 2013; Lawrence, Ryans, Sun, and Laptev 2018). This literature also focuses on the effects of attention on investor decision-making—such as purchasing attention-grabbing stocks (Barber and Odean 2008) and achieving better performance when paying more attention (Gargano and Rossi 2018). My paper suggests that the type of attention is relevant when mitigating behavioral biases, and that some attention (fast-thinking) makes biases worse. My results suggest that future researchers consider more closely the types of attention paid by investors.

Lastly, I contribute to the nascent literature on the effects of smartphone apps and their push notifications on retail traders' actions by showing that push notifications lead to stronger behavioral biases, such as the disposition effect. Other studies have found that push notifications lead investors to take more risk (Arnold et al. 2021) or to use stale, unscaled earnings surprise measures in their trading decisions (Moss 2022). Relatedly, my results have implications for investors and regulators. My paper adds to the discussion initiated by the SEC about whether and how to regulate online brokerages that use new technologies to attract users' attention (Michaels and Osipovich 2021). Brokerages claim their notifications help investors pay attention—implying that paying more attention increases investors' welfare (e.g., Robinhood 2016; Cruz 2019)—but my results call into question the assumption that all attention is good attention. In contrast, my results indicate that the type of attention induced by brokerage app push notifications is harmful and serves to exacerbate behavioral biases, leading to worse performance. Given the growing influence of retail traders in the capital markets (e.g., van der Beck and Jaunin 2021; McCabe 2021) and the role of retail brokerage smartphone applications as information intermediaries, my paper contributes a relevant finding to this growing field.

2. Literature Review and Hypothesis Development

2.1 Fast-thinking (System 1) and Slow-thinking (System 2) Attention

Kahneman (2011) summarizes a large body of work on decision-making under uncertainty. An overarching theme of this work is that humans have two mental processes called fast thinking (System 1) and slow thinking (System 2). These two systems work simultaneously in our brains and are characterized by different operations, biases, and thoughts.

Fast thinking operates automatically and quickly with little effort[1]. This system is akin to our intuition. For example the problem 2+2 generates an automatic response of 4 without having to exert any mental effort. Fast thinking involves associating new information with existing patterns or thoughts and often operates unconsciously. Important for my study, fast thinking falls prey to biases, such as anchoring, substitution, availability, loss aversion, framing, and the sunk cost fallacy (Kahneman 2011).

Slow thinking, on the other hand, is associated with effortful, strenuous mental work. Given the same inputs, slow thinking and fast thinking often arrive at different results. For example the problem 17x24 does not generate a response from fast thinking. Our fast-thinking attention must recruit the effortful slow-thinking attention to answer the problem. Because slow thinking requires effort, people prefer to let fast thinking make decisions unless fast thinking determines a need for slow thinking (Kahneman 2011). In this framework, fast-thinking biases persist because our

[1] Kahneman (2011) notes that the automatic fast thinking and effortful slow thinking (System 1 and System 2) do not exist in any material sense, and the two fictitious characters are instead shortcuts for describing how these systems induce people to take different actions. As he notes, "'[fast thinking] does X' is a shortcut for 'X occurs automatically.' And '[slow thinking] is mobilized to do Y' is a shortcut for 'arousal increases, pupils dilate, attention is focused, and activity Y is performed.'" I adopt similar language in my paper to discuss the two types of attention and their actions.

effortful slow-thinking attention has a limited capacity and humans only recruit its efforts when needed (Kahneman 2011).

2.2 The Disposition Effect

The disposition effect is the tendency of individual investors to sell stocks that have recently increased in value ("winners") and hold onto stocks that have recently decreased in value ("losers"). To illustrate how the behavior of an investor under the disposition effect differs from that of a rational investor, consider an investor who needs to sell stock for liquidity purposes, assuming efficient capital markets and no transaction costs. The investor has two investments: (i) Firm A closed the day before at $3,000 and is currently valued at $2,000, and (ii) Firm B closed the day before at $1,000 and is currently valued at $2,000. The rational investor sells stock in the firm that she expects to do more poorly (or less well) in the future. Assuming efficient markets (i.e., the investor cannot predict how the stocks will perform in the future), the rational investor sells daily gain or loss stocks with equal propensity.

A large body of research, however, shows that investors prefer to sell Firm B because its stock has increased 100% relative to the previous day, and the investors feel that they will "lock in" that gain. Kahneman (2011) claims that this bias is an instance of "narrow framing". Framing the problem with the previous day's closing price as the reference point (or similarly the purchase price) is irrelevant to a rational investor but changes the emotions of the human investor. Humans behave this way because of mental accounting, loss aversion, and the psychological ego boost of realizing a gain or the regret and ill feelings of realizing a loss (Shefrin and Statman 1985; Kahneman 2011).

The above discussion does not necessarily indicate that the disposition effect is irrational. If daily winners and losers perform just as well in the future (on average), it does not matter which investments retail investors sell. The literature, however, gives two reasons why the disposition effect is irrational and suboptimal (see Barber and Odean 2013 for a review). First, considering the effect of taxes on stock sales in most countries, the disposition effect increases the investor's tax bill (Shefrin and Statman 1985). A rational investor realizes her losses (i.e., sells losers) to lower her tax bill. Second, if we relax the assumption of efficient capital markets the disposition effect remains irrational. Research has shown that stocks that have performed well in the past tend to continue to do well in the future (the momentum effect, e.g., Jegadeesh and Titman 1993), suggesting that the optimal strategy is to sell losers and hold winners. In short, regardless of efficient or inefficient markets the disposition effect does not describe the actions of a rational decision-maker.

The existing evidence for the disposition effect is clear and best described graphically. Barber and Odean (2013) summarize the disposition effect literature and display two examples of this graph in their Figure 1, one of which I reproduce in Appendix A. Using personal individual investor trading data the studies graph—on the y-axis—the hazard ratio for the sale of stocks conditional on the return since original purchase—graphed on the x-axis (e.g., Barber and Odean 2013; Dhar and Zhu 2006; Grinblatt and Keloharju 2001). These graphs clearly show a higher slope on the right side (positive returns) compared to the left side (negative returns). This evidence suggests that investors prefer to sell stocks trading at a gain rather than stocks trading at a loss, controlling for the absolute return of the stock since purchase.

Although the disposition effect in individual investors is well documented, on average, less research focuses on the forces that mitigate or exacerbate this bias. Limited research suggests that more sophisticated investors and investors with more trading experience trade less in line with the disposition effect (Brown et al. 2006; Chen et al. 2007; Choe and Eom 2009; Barber et al. 2007; Dhar and Zhu 2006; Feng and Seasholes 2005; Seru, Shumway, and Stoffman 2010) and social interaction causes investors to trade more in line with the disposition effect (Heimer 2016). It is unclear, however, the relation between investor attention and the disposition effect, especially considering the different types of attention (fast-thinking and slow-thinking). My paper is the first to study how fast-thinking attention affects the disposition effect in investors.

2.3 Hypothesis Development

The psychology literature summarized above suggests that fast- and slow-thinking attention arrive at different decisions given the same inputs. The fast-thinking system quickly makes decisions; the slow-thinking system monitors and revises these decisions if the circumstances require or permit it. In this framework, when humans make a biased or irrational decision, their fast-thinking attention does the work without using their slow-thinking attention.

Researchers studying the disposition effect have offered several explanations, including some rational explanations (such as a belief in mean reversion, portfolio rebalancing, or informed trading; see Kaustia 2010) or psychologically biased explanations. These psychological explanations—prospect theory, regret aversion, narrow framing, mental accounting—are biases of human's fast-thinking attention (Kahneman 2011). Kahneman provides a framework in which these biases explain the existence of the disposition effect. The investors place their attention on a narrow frame—a stock's current price in reference to a somewhat arbitrary price in the past (yesterday's closing price or the purchase price). Then without their slow-thinking attention considering whether this reference point is relevant, the investor sells their winners and holds their losers because of the ego boost and emotional attachment of being a "good investor" who realizes gains, not losses (Shefrin and Statman 1985; Kahneman 2011). If these investors use their slow-thinking attention, however, they realize the irrelevance of the arbitrary reference point and ignore that information when making decisions.

It follows that if investors pay fast-thinking attention to a stock, they will trade more in line with the disposition effect. I state this hypothesis formally below:

H1: Fast-thinking attention exacerbates the disposition effect.

This hypothesis is not without tension, however. Fast-thinking attention often recruits the efforts of slow-thinking attention when warranted. If this recruiting occurs on average when investors consider selling investments, then the increased fast-thinking attention leads to increased slow-thinking attention, which will mitigate the disposition effect. Recently, researchers have demonstrated that investors who pay more attention to their portfolios—measured by how often they log into their online brokerage account and how long they stay logged into their account—trade less in line with the disposition effect (Dierick et al. 2019)[2]. As Dierick et al. note, these investors are also likely to be more sophisticated investors since they have a comparative advantage in understanding and incorporating financial information into decision-making. I argue that these investors likely pay more slow-thinking attention to their portfolios, thus explaining why the authors document a negative relation between attention and the disposition effect. If fast-thinking attention systematically recruits slow-thinking attention in investment decision-making, then I will not find evidence consistent with my hypothesis.

[2] I note that Dierick et al. (2019) measure attention based on the total amount of attention paid to an investor's portfolio during their entire sample period, including the number of days with a login, the total length of time the investor stayed logged in, and the number of distinct logins. It is difficult to tell, however, the *average* amount of time the investor stayed logged in, which could allude to the type of attention (fast- or slow-thinking) being paid during a specific login.

3. Research Design and Results

3.1 Smartphone push notifications

To test my research question, I develop a measure of fast-thinking attention by using the brokerage Robinhood's smartphone app push notifications. Smartphones are being increasingly used by sophisticated and retail investors to monitor information and trade (Miller and Skinner 2015), and those mobile trades impact liquidity and price discovery (Grant 2020; Brown, Stice, and White 2015). The growing trend of mobile trading introduced a new way for brokerages to attract their users' attention: the apps' push notifications. Push notifications are a relatively new technology; Apple introduced them in 2008 to their iPhones (Melanson 2008). The notifications are "pushed" from a backend server or application to a user interface, in most cases a user's smartphone screen. Users must agree to receive notifications through each app, and in most cases, users select the types of notifications they wish to receive. Research in fields such as health, education, or technology emphasize the suitability for push notifications to encourage consistent use of the app, which leads to the establishment of a habit (see Wohllebe 2020 for a review).

I contend that smartphone push notifications attract users' fast-thinking attention for two reasons. First, fast-thinking attention reacts quickly (Kahneman 2011), which makes it suitable for responding to push notifications. Survey evidence suggests that most smartphone users keep notifications always turned on and respond immediately to them (Alsayet et al. 2020). The ease and speed that a smartphone user responds to a push notification is unattractive to slow-thinking attention, which operates slowly and with more effort. Plus, these notifications externally stimulate users' attention, which involuntarily redirects the users' attention to a new task regardless of the users' intentions, goals, and beliefs (Theeuwes 1993; Arnold et al. 2021). Second, critics of push notifications and other digital technologies claim that "attention engineers" who create these products (e.g., social media, trading, and other apps) use the science of behavioral psychology to take advantage of cognitive biases and the weaknesses of the human brain (Newport 2019; TechDetox 2022). For example, Hartmans (2022) says certain apps mimic slot machines, and other apps take advantage of users' "fear of missing out" by encouraging streaks of daily use. Thus, smartphone app push notifications were created to attract fast-thinking attention.

3.2 Robinhood's price change notifications

Robinhood's price change push notifications are especially advantageous for testing my hypothesis. Robinhood is one of the largest retail brokerages in the U.S., supporting 18 million funded accounts and $81 billion in Assets Under Custody as of March 2021 (Robinhood Markets, Inc. 2021). Furthermore, Robinhood traders have a "substantial effect on stock prices" (van der Beck and Jaunin 2021) and had a large impact on the recent run-ups in "meme" stocks like GameStop and AMC in early 2021 (McCabe 2021). Given their growing influence, it is necessary to understand how Robinhood and other retail brokers influence their users' trading activity through their apps.

Robinhood sends its users standard price change push notifications with a clear, explicit frame. Many brokerages allow users to select their own price change notification thresholds; Robinhood only allows users to receive 5% and 10% price change notifications, and their app's notifications display returns in reference to the previous day's closing price. This limited option set allows the identification of the notification trigger (using publicly available market price data) and the reference point to document the disposition effect. Appendix B provides screenshots of the notification settings in the Robinhood app and an example of what a notification looks like on users' smartphone screens. Once a user receives the notification, it takes five taps on the screen to make a trade which can be done in under one minute. The ease and speed that an investor can trade after the notification also gives more support to these investors using their fast-thinking attention rather than using their slow-thinking attention.

I argue that Robinhood's app developers designed the app specifically with users' fast-thinking attention in mind. Robinhood has grown in popularity with retail investors by creating an interface that is easy to understand and does not have complex information that calls for slow thinking (Ingram 2019). Their push notification of daily price moves takes advantage of users' psychological bias of the framing effect, or narrow framing. Kahneman (2011) says that "different ways of presenting the same information often evoke different emotions." For example, comparing the current price to some arbitrary price in the past (the previous day's closing price) frames the problem in such a way that is different from comparing the current price to an analyst's target price. The reference point is an anchor that is irrelevant to a rational investor's decision to sell the stock—it does not make a difference as to what the investor expects the stock to do in the future (absent any momentum or other mispricing effects).

Based on this discussion, I argue that Robinhood's price change notifications are advantageous for studying the effects of fast-thinking attention on the disposition effect in retail traders. Studying Robinhood, however, could raise concerns of generalizability to other sets of investors or even other retail traders. Some studies and media articles show that Robinhood's users make significantly more trades and engage in more risk-taking than users of other retail platforms (e.g., Barber et al. 2021). I argue that this is the case because Robinhood's app is designed to induce more fast-thinking attention from its users. In this sense, Robinhood's users, who are most likely to use fast-thinking attention, are the most favorable investors to study my research question. If Robinhood users are significantly different from other groups of investors—in ways other than the type of attention they are likely to pay—the generalizability of my results will be limited.

3.2 Sample Selection

I start with all stocks traded on Robinhood using data obtained from Robintrack[3], a third-party data aggregator that scrapes ownership data from Robinhood. This data includes the number of Robinhood users who own a particular stock (but not the quantities) for approximately hourly intervals from May 2, 2018, to August 13, 2020. I then merge each stock-day to NYSE's Trade and Quote (TAQ) Trades file to determine the time the stock crosses an absolute 5% return from the previous day's closing price—triggering Robinhood to send price-change push notifications to owners of the stock. I follow Boehmer et al. (2021) to identify retail trading activity for each stock before and after the 5% price change triggers a notification. Boehmer et al. (2021) provide a novel way of identifying retail trades in TAQ based on two characteristics observable in the data. The trades occur off-exchange (exchange code "D" in TAQ) and are fulfilled by a wholesaler or market-maker who gives the retail investor sub-penny price improvement (e.g., a price of $45.001 represents a retail sale order that is given a 1/10 penny price improvement). This algorithm allows me to identify the number of retail sale trades around a Robinhood push notification.

Using this full sample of 5% daily movers, I calculate the percentage change in the number of retail sale trades from the one-hour period before the 5% trigger to the one-hour period after the 5% trigger. For example, if the stock trades at +5% for the first time at 12:05 PM, this measure (*PctChRetailSales*) is the number of retail sale trades from 12:05-1:05 minus the number of retail sale trades from 11:05-12:04, divided by the number of retail sale trades from 11:05-12:04. By using a percentage change, I alleviate concerns that treatment and control firms have significantly

[3] I thank Casey Primozic and Alex J of Robintrack.net for making this data available.

different levels of pre-trigger retail trading activity. For completeness, I also compute the raw change in retail sales without scaling (*ChRetailSales*).

I restrict my sample to stock-days that cross the 5% threshold between 10:35 AM ET and 2:55 PM ET. This window allows me to measure the level of trading activity when the market is open for one hour before the 5% trigger and one hour after the 5% trigger. Although Robinhood allows trading outside of market hours, it is illiquid. I measure trading activity over one-hour periods given Alsayed et al.'s (2020) evidence that most smartphone users react to notifications immediately and Arnold et al.'s (2019) evidence that most investors react to a push notification in less than 90 minutes. One hour is a reasonable amount of time for investors to react to the notification and allows for a sufficient sample size of 5% triggers within the trading day. A one-hour measurement period also limits the time for investors to use their slow-thinking attention, thereby making it more likely that I am capturing fast-thinking attention.

I exclude the first and last five minutes of the trading day from the measurement periods since these times are characterized by high trading activity that adds noise to my measurements. Lastly, by removing the 5% triggers that occur at the stock market open, I remove price swings that occur due to earnings announcements and other information released outside of market hours. Removing other sources of information alleviates the concern that other information releases cause the increased attention.

Lastly, I merge the dataset to Compustat for additional control variables including firm size, book-to-market, and SIC industry codes and drop observations missing control variables. I display my sample selection procedures in Table 1.

3.3 Descriptive Statistics

Table 2, Panel A provides descriptive statistics for the entire sample of absolute 5% return firm-days. The mean change in retail sales, trades, and purchases (all calculated analogous to sales described above) from the hour prior to the hour after the 5% trigger are all positive, which is consistent with prior literature that documents retail traders' attraction to volatile stocks (e.g., Myhre and Henriksen 2020; Weißofner and Wessels 2020). This statistic also underscores the importance of comparing stocks that have the same daily price path, since the price path itself attracts retail trading activity. Just under half of the notifications are positive 5% price changes (*Positive*); the rest are negative 5% price changes.

3.4 Sample of high and low Robinhood (fast-thinking attention) stocks

Robinhood investors receive push notifications after a 5% price change, increasing the level of fast-thinking attention in the stock—thus, I proxy for high fast-thinking attention in a stock with having a high level of Robinhood user ownership. I calculate the proportional level of Robinhood ownership by dividing the number of Robinhood owners at the beginning of the calendar day (from Robintrack) by the number of shares outstanding[4]. Then, I split this variable in two groups by the median, where *HighRH* = 1 for values above the median and 0 otherwise. Although not a perfect measure of Robinhood proportional ownership (since Robintrack's data does not include shares, just the number of owners), this variable captures firms with a higher

[4] Conceptually, the number of retail shareholders is a favorable scalar to measure the percentage ownership by Robinhood shareholders, since I examine total retail trading after a notification, but this data does not exist to my knowledge. Number of *total* shareholders does exist. I note that my primary results are robust to using this variable (from Compustat) as a scalar, however it is less populated in my sample and decreases my sample size by about 20%. To test whether my results are due to the choice of shares outstanding as a scalar, I replaced *HighRH* with a variable for below the median in shares outstanding, finding no significant results on my coefficient of interest in Table 5 (untabulated). It does not appear that my results are due to scalar choice.

proportional level of Robinhood user ownership and serves as my basis for high levels of fast-thinking attention after a 5% return.

Table 2, Panels B and C display descriptive statistics for the sample split on the *HighRH* variable. Notably the volume of retail trades in the past six months (from the trigger day) is higher for the high Robinhood sample by a factor greater than 3 (*AvgRetailVol6Mo*). This is not surprising. Robinhood is a retail brokerage—and Robinhood traders are attracted to firms that also attract other retail brokerage customers. It is necessary, therefore, to control for the general level of retail trading in the stocks in my sample.

Given the differences in retail trading activity between the high and low Robinhood firms, I entropy balance my sample on three plausibly endogenous firm characteristics. Entropy balancing constructs a set of matching weights for control observations with means, variances, and skews of covariates equal to the treatment sample (Hainmueller 2012; McMullin and Schonberger 2020). Most important, I balance the sample on the level of retail volume (using the Boehmer et al. 2021 algorithm) over the past six months (*AvgRetailVol6Mo*). I assume that by balancing the high and low Robinhood firms on this variable, I hold constant the level of retail trader ownership in the stock. Since I examine the disposition effect, this approach ensures that treatment and control firms have similar levels of retail investor ownership, but varying levels of Robinhood user ownership (who receive push notifications). I also balance the sample on firm size (*LogAssets* as of the most recent quarter) since Robinhood users likely make up a smaller portion of larger firms. Lastly, I include the firm's Book-to-Market ratio (*LogBTM* as of the most recent quarter) since firms with higher growth potential attract more retail traders (e.g., Barber and Odean 2013).

To provide support for the entropy balancing technique, Table 3, Panel A presents the results of a probit model of the determinants of *HighRH*. High Robinhood ownership is positively associated with the level of retail trading activity in the stock over the past six months, as expected. Robinhood ownership is also negatively associated with firm size, which suggests that Robinhood investors make up a smaller proportion of ownership as the firm gets larger. Lastly, as expected, Robinhood ownership is positively associated with Book-to-Market. Although this model provides descriptive evidence of Robinhood ownership, it also provides the basis for my entropy-balancing approach. The model has a pseudo R^2 of 16.2% and an area under the ROC curve of 76.80%, which is considered acceptable discrimination by Hosmer et al. (2013, sec. 5.2.4). I rely, therefore, on entropy-balancing to reduce concerns of selection bias or endogeneity. Table 3, Panels B and C display the mean, variance, and skewness of these covariates before and after balancing. After entropy balancing the distribution of the average retail volume in the past six months is held constant between both groups, as well as the firms' size and book-to-market ratio. In robustness testing, discussed in section 4, I use an alternative firm fixed-effects identification method to mitigate concerns of unobservable differences between treatment and control firms.

3.5 The Disposition Effect on Average

My study examines the disposition effect with respect to a common reference point: the previous day's closing price. Most media websites, news tickers, and brokerage trading applications list stocks and their daily returns most prominently, which provides an explicit reference point to study the disposition effect. With my sample of daily 5% price changes, I first examine whether investors trade in line with the disposition effect by testing whether retail investors increase their selling activity more after a positive daily price change than after a negative daily price change, holding the absolute value of the daily price change constant (i.e., comparing +5% to -5% and controlling for price changes within the one-hour pre- and post-measurement windows). This evidence would be consistent with the disposition effect: investors prefer to sell stocks that have recently increased in value and hold stocks that have recently decreased in value.

I first provide graphical univariate evidence of investors making more sale trades after a positive 5% price change compared to a negative 5% price change. In Figure 1, I restrict the sample to triggers that occur between 11:35 AM ET and 1:55 PM ET to observe the number of retail sale trades for two hours before and after the 5% trigger. I graph the percentage change in the number of retail sale trades from the second hour before the trigger (hour -2) separately for positive and negative 5% price changes. The graph clearly shows a higher increase in retail sales for positive price changes compared to negative price changes, consistent with the disposition effect.

I next turn to multivariate tests for evidence of the disposition effect. I follow prior literature and assume rational traders just as likely sell after a negative versus a positive 5% price change, assuming efficient markets (e.g., Kahneman 2011; Barber and Odean 2013). If the disposition effect manifests in this sample, then I will document a higher percentage change in retail sales after a positive 5% return compared to a negative 5% return. This result would provide evidence that investors prefer to sell their daily winners compared to their daily losers after controlling for other determinants of retail selling activity. I formally test this conjecture by estimating the following regression, equation 1:

$$ChRetailSales = \alpha + \beta_1 Positive + \boldsymbol{\Sigma\beta Controls} + \varepsilon,$$

where *ChRetailSales* is equal to either 1) the raw change or 2) the percentage change in the number of retail sale trades in the one-hour before the stock crosses an absolute daily 5% return (from the previous day's closing price) to the hour after the stock crosses 5%, as discussed above.

I include several control variables that are endogenous with price changes and influence retail trading activity. Since my sample period covers the COVID-19 pandemic lockdown period when retail investing increased dramatically (Ozik et al. 2021), I control for *Lockdown*, equal to one after the date of widespread lockdowns in the United States, March 20, 2020. Another significant determinant of retail trading activity is the current daily absolute return (Barber and Odean 2008; Barber et al. 2021). Although I hold constant across firm-days the absolute price change at the time of the trigger (5%), I also control for the return at the end of the one-hour measurement window. *AbsReturn1Hr* is equal to the absolute value of the return (relative to the previous day's closing price) at the time of the trigger plus one hour. I subtract 5% to measure the change in the return since the 5% return triggered a notification. I interact *Positive* with *AbsReturn1Hr* since the disposition effect predicts different levels of selling based on whether the absolute return is positive or negative. Since the speed that the stock's price increased or decreased 5% indicates differing levels of news, I control for the one-hour return retroactive from the trigger price (*AbsReturnPastHour*). A larger value of *AbsReturnPastHour* signifies that the stock quickly jumped over the absolute 5% threshold; lower values indicate a slower rise or fall during the day. I control for firm-size (*LogAssets*) and growth (*LogBTM*) since retail investors prefer larger, more visible, and higher growth firms. I control for the baseline level of retail trading activity in the stock with the average volume of retail trades in the previous six months from the 5% trigger day (*AvgRetailVol6Mo*). In this test, I control for high proportional Robinhood ownership (above median number of Robinhood owners divided by shares outstanding: *HighRH*) since Robinhood traders receive push notifications after the price change. Lastly, I control for retail traders' industry preferences with SIC 2-digit fixed effects, and I control for time trends with year-quarter fixed effects.

Retail investors trading in line with the disposition effect implies that they make more sale trades after a 5% increase in price than they make after a 5% decrease in price. As such, I predict a positive coefficient on *Positive*. Furthermore, as the absolute return reaches higher after initially crossing the 5% threshold, I expect retail investors to make more sale trades for the positive return stocks. In other words, holding the absolute return at the end of the measurement window (*AbsReturn1Hr*) constant, I expect retail investors to make more sale trades for the positive notification firms. This prediction manifests in a positive coefficient on *Positive*×*AbsReturn1Hr*.

In Table 4, I present the results of equation 1. In both columns the coefficient on *Positive* is significantly positive, providing evidence that retail traders make more sale trades after a positive 5% daily return compared to a negative 5% daily return. This evidence is also economically significant—positive 5% stocks have an increase in retail sales that is about 29.9% higher than the increase in retail sales for negative 5% stock returns, which is consistent with measures of the disposition effect in other settings (e.g., Kaustia 2010). Furthermore the coefficient on the interaction term *Positive*×*AbsReturn1Hr* is significantly positive, suggesting that given the same absolute post-trigger return, retail investors make more sale trades after a positive return compared to a negative return. These results provide evidence that investors trade in accordance with the disposition effect when measured as a daily return.

3.6 Does fast-thinking attention mitigate or exacerbate the disposition effect?

Finally, I test my primary hypothesis that fast-thinking attention exacerbates the disposition effect. I first provide univariate graphical evidence of fast-thinking attention leading to a higher increase in selling after a positive price change. In Figure 2, Panel A I split the change in retail sales for the positive sample (from Figure 1) into high and low Robinhood firms based on the *HighRH* variable. The graph clearly shows that retail investors increase their selling more for positive 5% stocks when they are paying more fast-thinking attention (i.e., after more investors receive push notifications). In Panel B, there is less evidence of any difference in retail selling for negative 5% stocks. Overall, these figures provide univariate evidence that fast-thinking attention exacerbates the disposition effect in retail investors.

I next turn to my multivariate analysis. Using the entropy balanced sample described above, I estimate the following regression, equation 2:

$$ChRetailSales = \alpha + \beta_1 HighRH + \beta_2 Positive + \beta_3 HighRH \times Positive + \boldsymbol{\Sigma\beta Controls} + \varepsilon,$$

where *ChRetailSales* represents either the raw or percentage change in retail sales as described above. This test is analogous to Table 4 with the addition of *HighRH*'s interaction with *Positive* and the inclusion of the entropy balancing technique. If fast-thinking attention exacerbates the disposition effect in retail investors, then β_3 will be significantly positive (higher change in selling after a positive price change for high fast-thinking stocks compared to low fast-thinking attention stocks). Furthermore, β_1 will be either insignificantly different from zero or significantly negative. A negative β_1 is consistent with a smaller change in selling after a negative price change for high Robinhood stocks compared to low Robinhood stocks. But since the disposition effect manifests in simply holding stocks with negative price changes, there may not be any significant difference in the change in selling activity between high and low Robinhood firms.

In Table 5, I present the results of this test. The first two columns do not entropy balance the sample; the 3rd and 4th column use the entropy balanced sample. In the first two columns, β_1 is significantly negative, consistent with less retail selling after a negative price change for stocks with high fast-thinking attention from investors. Furthermore, β_3 is significantly positive, consistent with more retail selling after a positive price change for stocks with high fast-thinking attention from investors. In column 3, β_1 is significantly positive, but I note that this column uses an unscaled measure as the dependent variable and this coefficient could be caused by more trading in high Robinhood stocks in general. Focusing on column 4, which uses the percentage change (the most restrictive test), I find that the coefficient on *HighRH* is insignificantly different from zero, suggesting that for negative 5% return days, high fast-thinking attention stocks have no difference in retail sale trades on average. Next, the coefficient on *Positive*×*HighRH* is significantly positive, confirming the unbalanced test that retail investors increase their selling activity more after a positive daily 5% return when paying more fast-thinking attention to the stock[5]. This effect is also economically significant—high Robinhood, positive 5% stocks have an increase in retail sales that is higher than low Robinhood, positive 5% stocks by about 11.3%.

Taken together, these findings support my prediction that fast-thinking attention serves to exacerbate the disposition effect in investors. This result stands in contrast to prior literature that suggests that (arguably slow-thinking) attention mitigates the disposition effect (Dierick et al. 2019). In short, these results suggest that researchers consider the type of attention when examining the relation between investor attention and trading outcomes.

[5] To alleviate concerns that the entropy balancing technique overweight certain control observations, I note that my results are robust (untabulated), and even stronger, when I drop control observations above the 99th percentile of weights (4.71).

4. Additional Analyses and Robustness

4.1 Do investors trade less in line with the disposition effect if they are more likely using slow-thinking attention?

In my primary analysis, investors react to a push notification quickly and are likely to use their fast-thinking attention. Investors who trade later in the day after receiving a push notification are more likely to be recruiting the efforts of their slow-thinking attention. This in turn may reduce their tendency to trade in line with the disposition effect. I test this presumption by examining the second hour after the 5% trigger, when investors have more time to use their slow-thinking attention. In this test, I calculate the change in the number of retail sales from the one-hour period immediately before the trigger to the second hour after the trigger (e.g., from 1:30 PM – 2:30 PM for a 12:30 PM trigger). In this test, I restrict my sample to triggers that occur before 1:55 PM ET so I can measure retail trading activity during market hours.

Table 6 presents the results. The coefficients on the interaction term of interest are all significantly lower than the coefficients in Table 5 using a seemingly unrelated regressions estimation (untabulated). The coefficient in the final column is also insignificantly different from zero at conventional levels, suggesting that the tendency for investors to trade in line with the disposition effect dissipates over time as more investors are likely to use their slow-thinking attention. This result provides further support for the push notification triggering fast-thinking attention, and fast-thinking attention increasing users' likelihood of selling their winning stocks, but as they are more likely to recruit the efforts of slow thinking the effect dissipates.

4.2 Do stocks that cross a positive 5% daily return achieve subsequent positive returns?

I provide evidence that retail investors sell stocks that are up 5% daily and sell more when they are using their fast-thinking attention. A natural question, then, is whether this behavior is suboptimal—i.e., whether the positive 5% stocks continue to achieve positive returns in the future. Momentum studies generally measure the return over one to six months and show that winners over that period tend to continue to increase in value in the future, and losers continue to decrease in value (e.g., Jagadeesh and Titman 1993). It is less clear, however, if momentum effects are still present when examining shorter-window (i.e., daily) price movements. Little research has studied the momentum (or reversal) of daily price changes. Xu (2017) finds that price movements in the morning positively predict future returns. This finding is relevant since my study focuses on price movements that occur intra-day and a significant portion of price movements that trigger a 5% price change notification occur in the morning (Median time of 5% trigger in my sample is 12:02 PM ET).

To address this question, I collect the subsequent 7, 30, 60, 90, and 120-day buy-and-hold abnormal (size decile adjusted) returns starting from the day after the 5% trigger for the full sample of positive 5% daily movers. I run a one-sample T-test to test whether the subsequent buy-and-hold abnormal returns are statistically greater than zero. In Table 7, this test shows that the positive 5% return stocks continue to achieve positive abnormal returns, on average, up to 120 days after the trigger day. This evidence, although descriptive, suggests that retail investors selling daily winners miss out on subsequent momentum.

4.3 Robustness to Extreme Continuation Returns

One potential concern with my methodology is that previous studies have documented that extreme stock returns are a significant determinant of retail trading activity, and news sources and the Robinhood app provide lists of the stocks each day with the largest absolute returns (Weißofner and Wessels 2020; Barber et al. 2021). In my primary analysis, I alleviate this concern by controlling for the absolute value of the continuation return (i.e., the return at the end of the one-hour measurement window) and its interaction with *Positive*. This approach, however, may not adequately control for extreme returns if its relation is non-linear with retail trading activity. To further bolster the robustness of my main results, I estimate the regressions of Table 5 without observations that have extreme continuation returns.

Specifically, in Table 8, I systematically drop observations where at the end of the one-hour period the daily return of the stock exceeds absolute 10%, then 9%, and so on, to 6%. Thus, in the final column the sample includes stock-days that crossed an absolute 5% threshold but subsequently stayed below an absolute 6% threshold within one hour after the trigger. Thus the returns in these tests are only just extreme enough to trigger a Robinhood push notification but are less likely to be included on daily mover lists or otherwise attract attention. With this more restrictive sample, I continue to find results consistent with a stronger disposition effect for stocks with a high level of fast-thinking attention from investors.

4.4 Placebo Test: Robinhood Outages

During my sample period, Robinhood's application suffered several outages that restricted trading or otherwise halted the entire Robinhood ecosystem (see, e.g., Friedman and Zeng 2021). During these outages, I presume that either price change push notifications were not sent to users, or the users could not trade after receiving a push notification. Robinhood outages therefore provide a natural placebo test for my analysis. In this test, I restrict my sample to 5% triggers that occur during the seven outages listed in Friedman and Zeng (2021) and re-estimate equation 2.

Table 9 presents the results. None of the coefficients of interest are statistically significantly different from zero. I note however that the sample in this test is much smaller than the sample in my primary analyses due to the limited number of Robinhood outages. This test nonetheless provides a placebo test during times when stocks achieved a 5% return, but Robinhood's app did not induce users to increase their level of fast-thinking attention to the stocks in question.

4.5 Firm Fixed Effects Model

Although the identification approach used in my primary tests control for endogeneity and selection issues, there may be unobservable firm characteristics that vary between the treatment and control groups that could explain the results of my tests. To alleviate these concerns, I turn to an alternative research design using firm fixed effects.

This identification strategy compares retail trading activity within-firm after a 5% return during a period when Robinhood sends notifications through their app to a period before Robinhood started sending notifications. According to Robinhood's blog, they started sending push notifications using their app in February 2016 (Robinhood 2016). In this test, I examine a sample of firms with a high level of Robinhood ownership during the period that I have Robinhood ownership data, which covers 2018-2020. First, I take the average of the number of Robinhood owners divided by shares outstanding during this period. I keep in my sample the firms that have above the 75th percentile of Robinhood ownership and collect the retail trading activity before and after 5% returns for a sample period of 2014-2015 (pre-Robinhood notifications) and 2018-2019 (post-Robinhood notifications). This post-period allows for enough time for a significant number of Robinhood investors to opt into receiving push notifications after their introduction. My dependent variables (change and percentage change in retail sale trades) remain the same as the previous analysis.

Although this design controls for any time-invariant firm characteristics, it does not control for changes in the firm and its retail investor (or Robinhood owner) makeup between the two periods. In these tests, I assume that Robinhood ownership and the unobservable characteristics that determine Robinhood ownership are consistent across the two periods, which may not be true. Unfortunately the Robinhood ownership data only covers a period that Robinhood sent out push notifications. To mitigate concerns of changing retail investor behavior within-firm over these two periods, I include as a control variable the past six month's average daily retail trading volume. For the reasons mentioned above, I also remove the observation if the 5% return trigger occurs before 10:35 AM ET or after 2:55 PM ET.

Table 10 displays the results. *Post* is equal to one in the period after Robinhood started sending push notifications and equal to zero for the period without push notifications. All other variables are analogous to my previous tests. In this test, *Post* measures high fast-thinking attention by investors after a 5% price change. Using this alternative research design, my results remain consistent. The coefficient on *Positive* and *Post*×*Positive* are both significantly positive, consistent with retail traders increasing their selling activity more after a positive return when they are more likely to pay fast-thinking attention to the stock.

5 Conclusion

In this paper, I provide evidence that fast-thinking attention exacerbates the disposition effect in retail investors. By studying Robinhood's price change push notifications, I document that stocks that have a higher level of Robinhood ownership have larger increases in retail selling activity after a positive 5% return triggers Robinhood to send notifications to owners of the stock. These findings contrast with prior literature that finds that attention mitigates the disposition effect (Dierick et al. 2019), which—because of their focus on investor logins to online brokerage accounts—likely captures slow-thinking attention. My findings suggest that future research consider the types of investor attention when examining how attention affects decisions.

Finally, retail brokerages claim that their push notifications help investors pay more attention to their portfolios and to the markets. My findings suggest that the type of attention paid after push notifications likely cause worse decisions than if investors paid no attention at all. These results add to the discussion initiated by the SEC in determining how to regulate these online app-based brokerages and trading apps.

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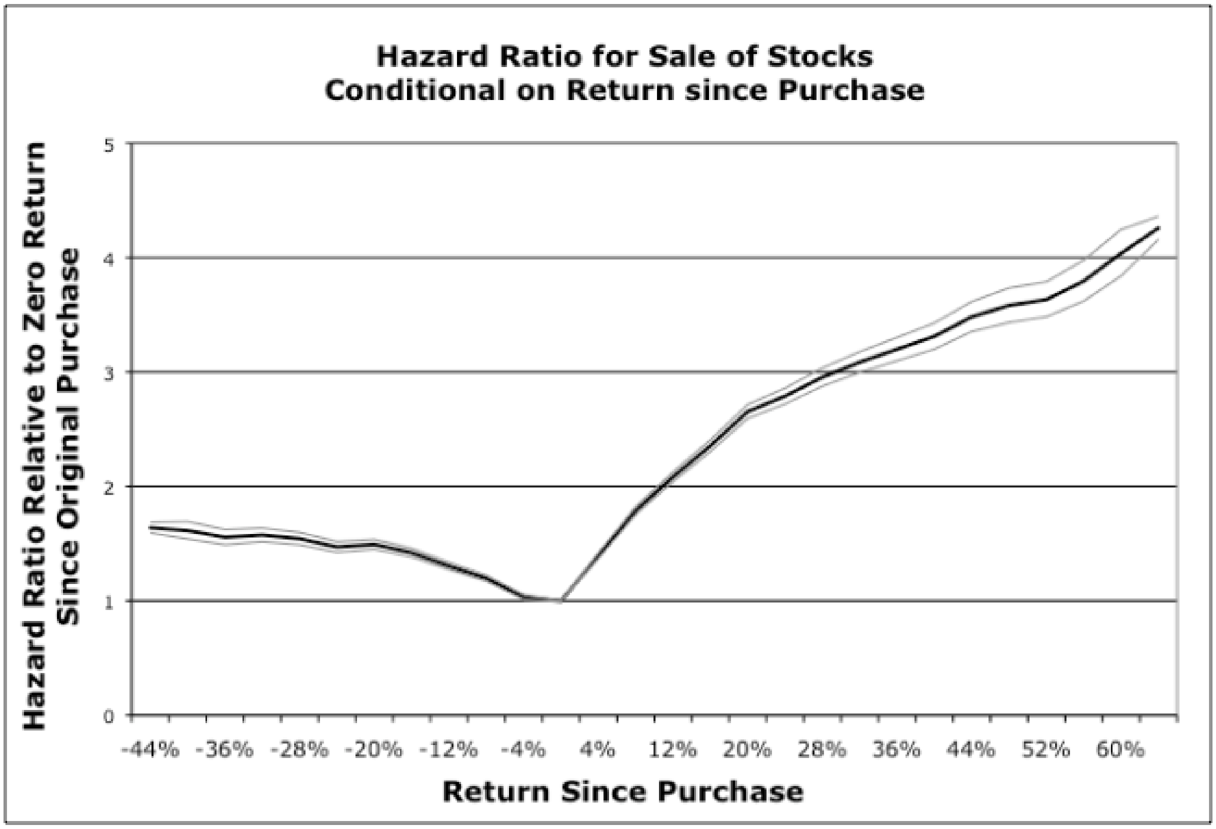
Appendix A- Figure 1, Panel A of Barber and Odean (2013)

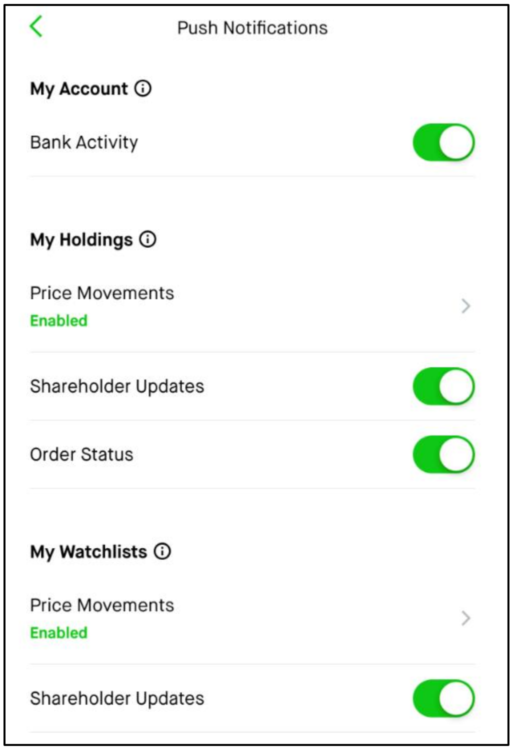
Figure 1: The disposition effect
Panel A: Large Discount Brokerage, 1991 to 1996



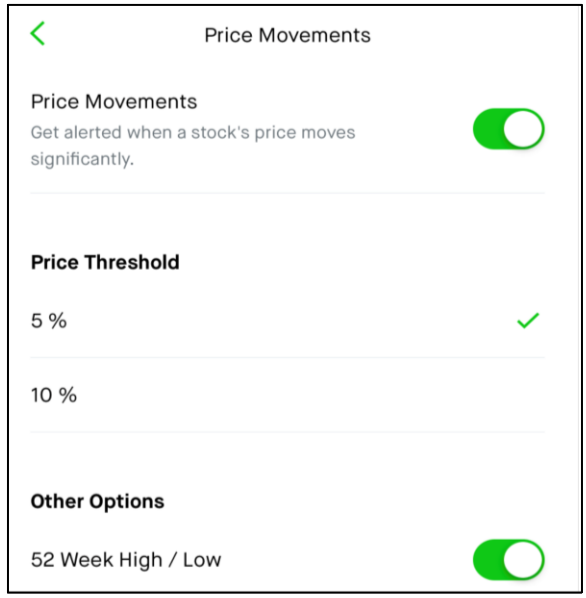
Notes: This figure is Figure 1, Panel A of Barber and Odean (2013) and is not my original work. Using individual-level brokerage data, the graph depicts the propensity to sell a stock (y-axis) based on the return since purchase (x-axis). Reprinted from Handbook of the Economics of Finance, Vol 2, Part B, Brad M. Barber and Terrance Odean, Chapter 22- The Behavior of Individual Investors, Page No. 47, Copyright (2013), with permission from Elsevier.

Appendix B: Robinhood Push Notification Options and Example

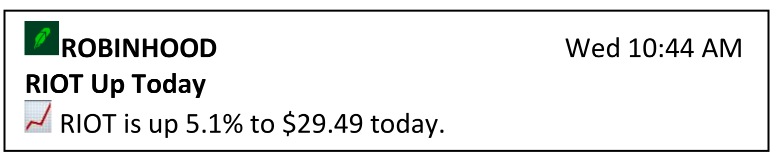
Panel A:



Panel B:



Panel C:



Notes: This appendix includes two screenshots from an iPhone displaying the Robinhood trading app, and one screenshot showing an example of a push notification like the ones studied in this paper. Panel A displays the push notification options, and Panel B displays the specific price movement notification options. Panel C includes a depiction of one of the price change notifications that appears on users' smartphone home screen. When the notification is tapped by the smartphone user, the trading application opens to the firm's page showing the day's price chart, allowing the investor to make trades in the stock. The screenshots included here were taken in July 2021, and I confirmed with Robinhood investors that the notification options were the same during the sample period studied in this paper.

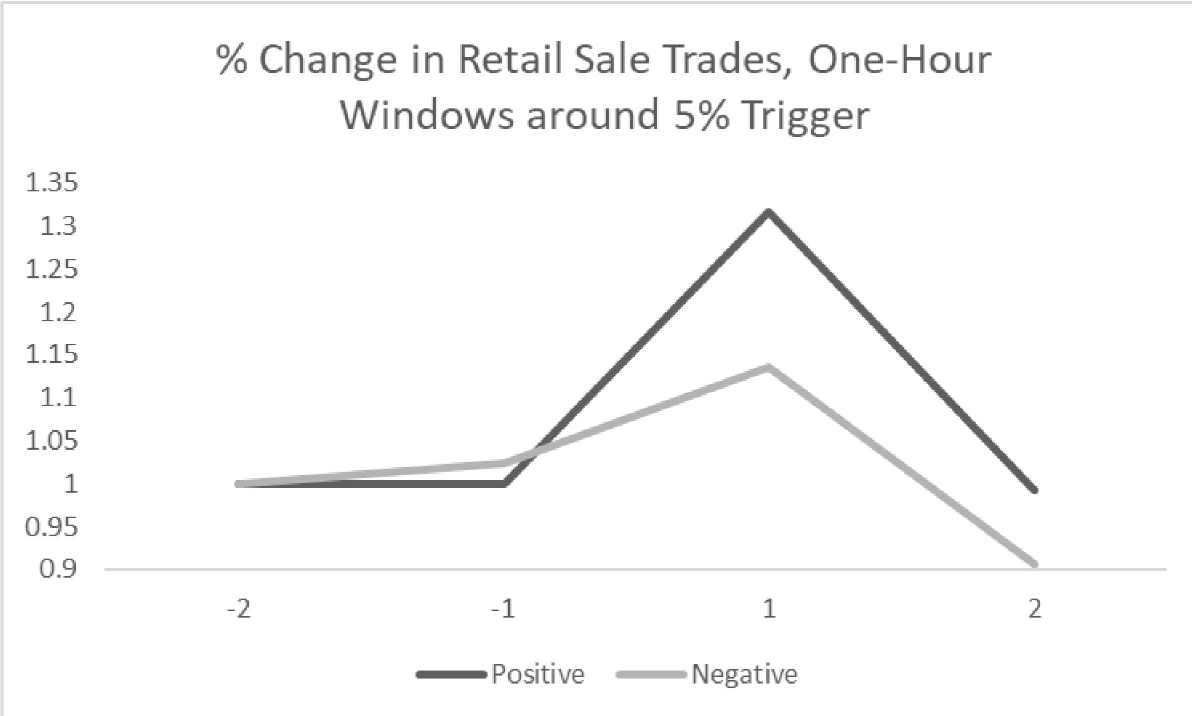
Appendix C- Variable Definitions

Variable Definitions	
ChRetailSales	The number of retail sale trades (following Boehmer et al. 2021) in the one-hour period after the first absolute 5% trade of the day (measured based on the previous day's closing price) minus the number of retail sale trades in the one-hour period before the first absolute 5% trade of the day.
PctChRetailSales	*ChRetailSales* divided by the number of retail sale trades in the one-hour period before the first absolute 5% trade of the day. This variable captures the percentage change in the number of retail sale trades from before to after the 5% trigger. If *ChRetailSales* > 0 and the number of retail sale trades in the one-hour period before the first absolute 5% trade of the day = 0, then the value of this variable is replaced with 1 to represent a 100% increase in retail sales. If there are no retail sale trades in either the pre- or the post-trigger hour, then this variable is equal to 0.
ChRetailBuys	The number of retail buy trades (following Boehmer et al. 2021) in the one-hour period after the first absolute 5% trade of the day (measured based on the previous day's closing price) minus the number of retail buy trades in the one-hour period before the first absolute 5% trade of the day.
PctChRetailBuys	*ChRetailBuys* divided by the number of retail buy trades in the one-hour period before the first absolute 5% trade of the day. This variable captures the percentage change in the number of retail buy trades from before to after the 5% trigger. If *ChRetailBuys* > 0 and the number of retail buy trades in the one-hour period before the first absolute 5% trade of the day = 0, then the value of this variable is replaced with 1 to represent a 100% increase in retail buys. If there are no retail buy trades in either the pre- or the post-trigger hour, then this variable is equal to 0.
ChRetailTrades	The number of retail trades (following Boehmer et al. 2021) in the one-hour period after the first absolute 5% trade of the day (measured based on the previous day's closing price) minus the number of retail trades in the one-hour period before the first absolute 5% trade of the day.
PctChRetailTrades	*ChRetailTrades* divided by the number of retail trades in the one-hour period before the first absolute 5% trade of the day. This variable captures the percentage change in the number of retail trades from before to after the 5% trigger. If *ChRetailTrades* > 0 and the number of retail trades in the one-hour period before the first absolute 5% trade of the day = 0, then the value of this variable is replaced with 1 to represent a 100% increase in retail trades. If there are no retail trades in either the pre- or the post-trigger hour, then this variable is equal to 0.

LogAssets	Natural log of one plus total assets measured as of the most recent fiscal quarter end date.
AvgRetailVol6Mo	Average of the daily total retail volume (Boehmer et al. 2021) in the stock for the previous six months, measured from the day of the observation.
LogBTM	Natural log of one plus (total assets minus total liabilities)/(stock price times number of shares outstanding), measured as of the most recent fiscal quarter end date.
Positive	Equal to one if the observation is a positive 5% daily price change; equal to 0 if the observation is a negative 5% daily price change.
HighRH	Equal to one if the number of Robinhood owners (from Robintrack, as of the beginning of the day) divided by number of shares outstanding (Compustat, as of the most recent quarterly report) is greater than or equal to the median; zero otherwise.
Lockdown	Equal to one if the observation date is on or after March 20, 2020, the day of widespread COVID-19 stay-at-home orders in the United States. Note that the sample ends in August 2020 when stay-at-home orders were still in place in much of the country.
AbsReturn1Hr	Absolute value of the return at the end of the one-hour measurement period (one hour after the stock first crossed an absolute 5% daily return). This return is measured as of the previous day's closing price, and then 0.05 is subtracted from the value to normalize at 0.
AbsReturnPastHour	Absolute value of the return, retroactive from the 5% trigger time, of the past hour of the stock. This variable captures the speed that the stock crosses the 5% return threshold. For example, if the stock crosses +5% at 2:05 PM, this variable captures the absolute value of the return from 1:05 PM to 2:05 PM. Higher values indicate the stock jumped over 5% quickly; lower values indicate a much slower climb for the stock.
Post	Equal to one if the observation is in 2018 or 2019 (the period after Robinhood started sending push notifications to users of their app); zero otherwise (Table 10 only).

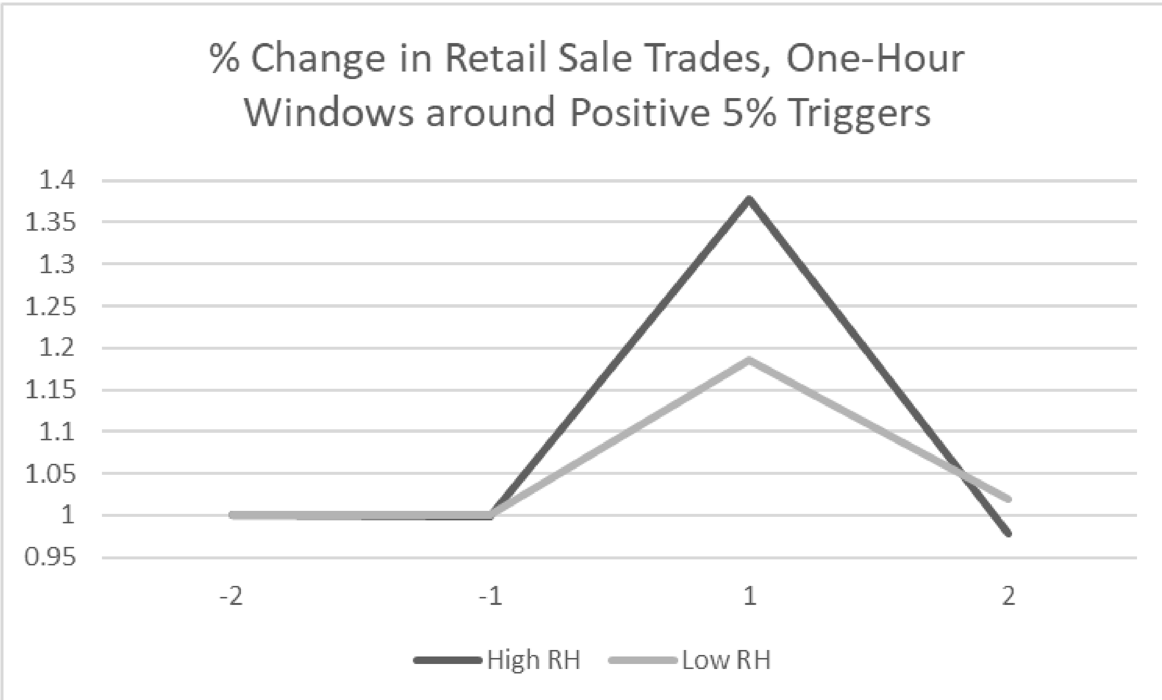
Notes: All continuous variables are winsorized at the 1% and 99% levels to reduce the influence of outliers.

Figure 1- The Disposition Effect on Average



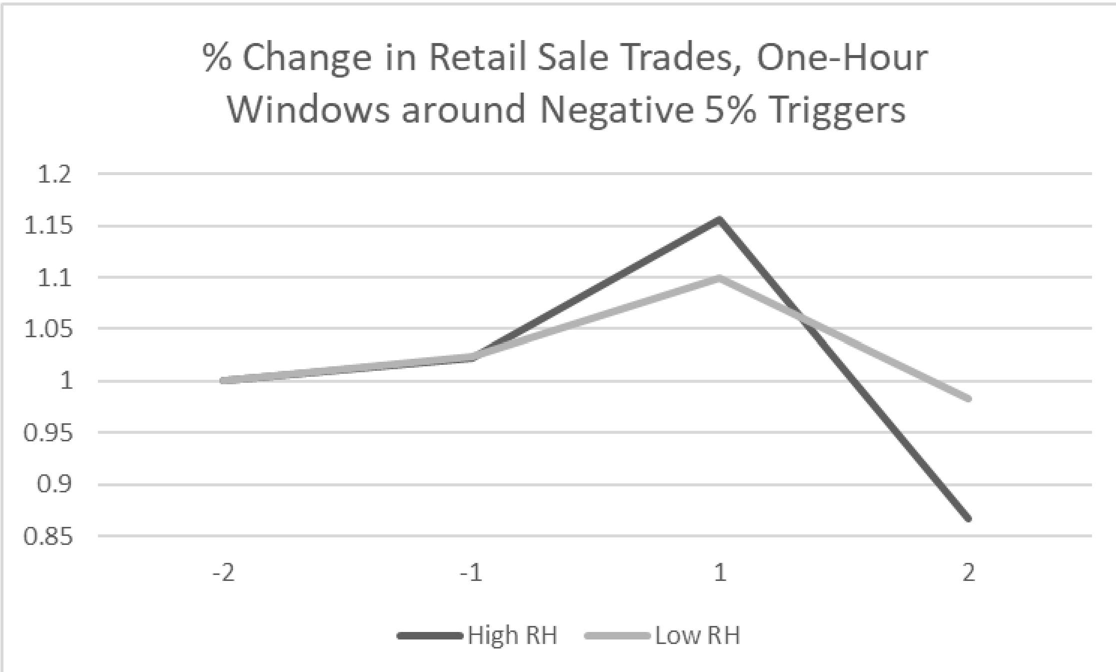
Notes: Figure 1 depicts the average percentage change in the number of retail sale trades in each hour relative to the 5% trigger time. The x-axis depicts the time relative to the 5% trigger (t=0), which is the first trade in the day where the stock trades at or above an absolute 5% daily return from the previous day's closing price. The value of -2 represents the one-hour period from two hours prior to the 5% trigger to one hour prior to the 5% trigger; -1 represents the one-hour period from one hour prior to the 5% trigger to the 5% trigger; 1 represents the one-hour period from the 5% trigger to one hour after the 5% trigger; 2 represents the one-hour period from one hour after the 5% trigger to two hours after the 5% trigger. The sample includes all firms traded on Robinhood (included in the Robintrack data) over the period May 2, 2018, to August 13, 2020, where the 5% trigger occurs between 11:35 AM ET and 1:55 PM ET to ensure that each hour measured is during normal market trading hours and removing from measurement the first and last five minutes of the trading day. The y-axis depicts the average percentage change in the number of retail sale trades in each hour, relative to the -2 hour. The number of retail sale trades in the stock each hour, in other words, is scaled by the number of retail sale trades in the -2 hour. The sample includes 38,371 positive 5% trigger stock-days and 42,031 negative 5% trigger stock-days.

Figure 2, Panel A- Change in Retail Sales Around Positive 5% Daily Price Changes between High and Low Robinhood Stocks



Notes: Figure 2, Panel A depicts the average percentage change in the number of retail sale trades in each hour relative to the positive 5% trigger time. The x-axis depicts the time relative to the positive 5% trigger (t=0), which is the first trade in the day where the stock trades at or above +5% daily return from the previous day's closing price. The value of -2 represents the one-hour period from two hours prior to the 5% trigger to one hour prior to the 5% trigger; -1 represents the one-hour period from one hour prior to the 5% trigger to the 5% trigger; 1 represents the one-hour period from the 5% trigger to one hour after the 5% trigger; 2 represents the one-hour period from one hour after the 5% trigger to two hours after the 5% trigger. The sample includes all firms traded on Robinhood (included in the Robintrack data) over the period May 2, 2018, to August 13, 2020, where the positive 5% trigger occurs between 11:35 AM ET and 1:55 PM ET to ensure that each hour measured is during normal market trading hours and removing from measurement the first and last five minutes of the trading day. The y-axis depicts the average percentage change in the number of retail sale trades in each hour, relative to the -2 hour. The number of retail sale trades in the stock each hour, in other words, is scaled by the number of retail sale trades in the -2 hour. The sample includes 38,371 positive 5% trigger stock-days total, split by high (19,270 stock-days) and low (19,101 stock-days) Robinhood ownership. High Robinhood ownership firms are those where the number of Robinhood owners (from Robintrack) divided by the number of shares outstanding (from Compustat) is equal to or greater than the median of that variable; Low Robinhood ownership firms are those where the number of Robinhood owners divided by the number of shares outstanding is less than the median of that variable.

Figure 2, Panel B- Change in Retail Sales Around Negative 5% Daily Price Changes between High and Low Robinhood Stocks



Notes: Figure 2, Panel A depicts the average percentage change in the number of retail sale trades in each hour relative to the negative 5% trigger time. The x-axis depicts the time relative to the negative 5% trigger (t=0), which is the first trade in the day where the stock trades at or above -5% daily return from the previous day's closing price. The value of -2 represents the one-hour period from two hours prior to the 5% trigger to one hour prior to the 5% trigger; -1 represents the one-hour period from one hour prior to the 5% trigger to the 5% trigger; 1 represents the one-hour period from the 5% trigger to one hour after the 5% trigger; 2 represents the one-hour period from one hour after the 5% trigger to two hours after the 5% trigger. The sample includes all firms traded on Robinhood (included in the Robintrack data) over the period May 2, 2018, to August 13, 2020, where the negative 5% trigger occurs between 11:35 AM ET and 1:55 PM ET to ensure that each hour measured is during normal market trading hours and removing from measurement the first and last five minutes of the trading day. The y-axis depicts the average percentage change in the number of retail sale trades in each hour, relative to the -2 hour. The number of retail sale trades in the stock each hour, in other words, is scaled by the number of retail sale trades in the -2 hour. The sample includes 42,031 negative 5% trigger stock-days total, split by high (20,396 stock-days) and low (21,635 stock-days) Robinhood ownership. High Robinhood ownership firms are those where the number of Robinhood owners (from Robintrack; as of that morning) divided by the number of shares outstanding (from Compustat; as of the most recent fiscal quarter end) is equal to or greater than the median of that variable; Low Robinhood ownership firms are those where the number of Robinhood owners divided by the number of shares outstanding is less than the median of that variable.

Table 1- Sample Selection

Robintrack Firm-Days	5,893,410
Days under 5% return	(5,151,626)
Crosses 5% outside of 10:35 AM - 2:55 PM ET	(539,147)
Missing Control Variables	(33,476)
Sample Size	169,161

Notes: Table 1 describes my sample selection procedures. Using the Robintrack data, which covers May 2, 2018-August 13, 2020, I first convert the data into firm-day observations. Then, I merge the dataset to TAQ and remove all observations where the stock does not trade higher than an absolute 5% return on the day (measured relative to the previous day's closing price). I then remove observations where the 5% trigger time is not between 10:35 AM ET and 2:55 PM ET. Lastly, I merge the dataset to Compustat for relevant control variables (total assets, market value of equity, book-to-market, SIC industry code) and drop observations where there is no match. The resulting 169,161 firm-day observations make up my main sample used in Tables 2-6.

Table 2, Panel A- Descriptive Statistics, Full Sample

Variable	N	Mean	SD	Min	Median	Max
ChRetailSales	169,161	4.71	28.04	-82	1	176
PctChRetailSales	169,161	0.62	1.86	-1	0.04	12
ChRetailBuys	169,161	5.70	31.59	-87	1	208
PctChRetailBuys	169,161	0.60	1.73	-1	0.05	11
ChRetailTrades	169,161	10.33	54.49	-146	1	363
PctChRetailTrades	169,161	0.61	1.72	-1	0.11	11
LogAssets	169,161	6.12	2.13	1.86	6.00	11.74
AvgRetailVol6Mo	169,161	0.11	0.29	0.00	0.03	2.15
LogBTM	169,161	0.52	0.60	-7.01	0.39	3.57
Positive	169,161	0.48	0.50	0	0	1
HighRH	169,161	0.50	0.50	0	0	1
Lockdown	169,161	0.31	0.46	0	0	1
AbsReturn1Hr	169,161	0.00	0.02	-0.05	0.00	0.06
AbsReturnPastHour	169,161	0.03	0.02	0	0.03	0.09

Notes: Table 2, Panel A describes the main sample. Using the Robintrack data, which covers May 2, 2018- August 13, 2020, I first convert the data into firm-day observations. Then, I merge the dataset to TAQ and remove all observations where the stock does not trade higher than an absolute 5% return on the day (measured relative to the previous day's closing price). I then remove observations where the 5% trigger time is not between 10:35 AM ET and 2:55 PM ET. Lastly, I merge the dataset to Compustat for relevant control variables (total assets, market value of equity, book-to-market, SIC industry code) and drop observations where there is no match. Variables are defined in Appendix C. This paper is interested in retail selling activity, however buying and trading activity is included here for completeness. All continuous variables are winsorized at the 1% and 99% levels.

Table 2, Panel B- Descriptive Statistics, High Robinhood Sample

Variable	N	Mean	SD	Min	p50	Max
ChRetailSales	84,384	7.10	34.84	-82	1	176
PctChRetailSales	84,384	0.71	1.98	-1	0.11	12
ChRetailBuys	84,384	9.08	39.71	-87	1	208
PctChRetailBuys	84,384	0.69	1.83	-1	0.14	11
ChRetailTrades	84,384	16.09	68.52	-146	2	363
PctChRetailTrades	84,384	0.66	1.74	-1	0.16	11
LogAssets	84,384	5.39	2.02	1.86	5.20	11.74
AvgRetailVol6Mo	84,384	0.17	0.37	0.00	0.05	2.15
LogBTM	84,384	0.48	0.64	-6.89	0.32	3.57
Positive	84,384	0.49	0.50	0	0	1
Lockdown	84,384	0.34	0.47	0	0	1
AbsReturn1Hr	84,384	0.00	0.02	-0.05	0.00	0.06
AbsReturnPastHour	84,384	0.03	0.02	0	0.03	0.09

Table 2, Panel C- Descriptive Statistics, Low Robinhood Sample

Variable	N	Mean	SD	Min	p50	Max
ChRetailSales	84,777	2.32	18.71	-82	0	176
PctChRetailSales	84,777	0.54	1.73	-1	0	12
ChRetailBuys	84,777	2.34	19.97	-87	0	208
PctChRetailBuys	84,777	0.51	1.62	-1	0	11
ChRetailTrades	84,777	4.60	34.43	-146	1	363
PctChRetailTrades	84,777	0.57	1.71	-1	0.06	11
LogAssets	84,777	6.84	2.00	1.86	6.88	11.74
AvgRetailVol6Mo	84,777	0.06	0.17	0.00	0.01	2.15
LogBTM	84,777	0.55	0.55	-7.01	0.45	3.57
Positive	84,777	0.48	0.50	0	0	1
Lockdown	84,777	0.27	0.44	0	0	1
AbsReturn1Hr	84,777	0.00	0.02	-0.05	0.00	0.06
AbsReturnPastHour	84,777	0.03	0.02	0	0.03	0.09

Notes: Table 2, Panel B describes the sample of high Robinhood firm stock-days; Table 2, Panel C describes the sample of low Robinhood firm stock-days. High Robinhood ownership firms are those where the number of Robinhood owners (from Robintrack; as of that morning) divided by the number of shares outstanding (from Compustat; as of the most recent fiscal quarter end) is equal to or greater than the median of that variable; Low Robinhood ownership firms are those where the number of Robinhood owners divided by the number of shares outstanding is less than the median of that variable.

Table 3, Panel A- Determinants of *HighRH*

	(1)
DEPVAR=	*HighRH*
LogAssets	-0.289***
	(-29.089)
AvgRetailVol6Mo	2.049***
	(9.734)
LogBTM	0.037
	(1.336)
Constant	1.543***
	(24.234)
Observations	169,161
Psuedo R-squared	0.162

Table 3, Panel B- Before Entropy Balancing

	HighRH = 1			*HighRH* = 0		
	Mean	Variance	Skewness	Mean	Variance	Skewness
LogAssets	5.395	4.088	0.544	6.841	3.983	0.152
AvgRetailVol6Mo	0.170	0.133	3.985	0.058	0.028	7.279
LogBTM	0.482	0.411	1.511	0.550	0.303	1.980

Table 3, Panel C- After Entropy Balancing

	HighRH = 1			*HighRH* = 0		
	Mean	Variance	Skewness	Mean	Variance	Skewness
LogAssets	5.395	4.088	0.544	5.395	4.089	0.545
AvgRetailVol6Mo	0.170	0.133	3.985	0.170	0.133	3.985
LogBTM	0.482	0.411	1.511	0.482	0.411	1.511

Notes: Table 3, Panel A presents the results of a Probit regression with *HighRH* as the dependent variable. *HighRH* =1 if the number of Robinhood owners (from Robintrack; as of that morning) divided by the number of shares outstanding (from Compustat; as of the most recent fiscal quarter end) is equal to or greater than the median of that variable; 0 otherwise. All variables are defined in Appendix C. Robust z-statistics are in parentheses. Standard errors are clustered by firm. Statistical significance is denoted by *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The area under the ROC curve is 0.7679 which is considered acceptable discrimination by Hosmer, Lemenshow, and Sturdivant (2013, sec. 5.2.4). The results provide support for my entropy balancing technique used in tables 5-9. Panel B presents the distribution of the entropy balancing variables before entropy balancing weights are applied to the control observations; Panel C presents the distribution of the variables after the weights are applied to the control observations.

Table 4- The Disposition Effect on Average

	(1)	(2)
DEPVAR=	*ChRetailSales*	*PctChRetailSales*
Positive	4.125***	0.299***
	(21.920)	(26.568)
AbsReturn1Hr	237.630***	12.106***
	(27.006)	(30.634)
Positive ×*AbsReturn1Hr*	38.417***	3.911***
	(4.282)	(6.631)
HighRH	2.137***	0.011
	(10.609)	(0.867)
LogAssets	0.059	-0.090***
	(0.824)	(-23.521)
AvgRetailVol6Mo	18.458***	-0.004
	(17.365)	(-0.210)
LogBTM	-0.856***	0.045***
	(-5.127)	(4.273)
AbsReturnPastHour	50.263***	5.000***
	(9.647)	(17.941)
Constant	-0.495	0.924***
	(-0.462)	(16.830)
Observations	169,161	169,161
Industry FE	Yes	Yes
Year-Quarter FE	Yes	Yes
Adjusted R-squared	0.0786	0.0441

Notes: Table 4 presents the results of the estimation of Equation 1, which tests for the disposition effect in my sample on average. The sample includes all firms traded on Robinhood (included in the Robintrack data) over the period May 2, 2018, to August 13, 2020, where the 5% trigger occurs between 10:35 AM ET and 2:55 PM ET to ensure that each hour measured is during normal market trading hours and removing from measurement the first and last five minutes of the trading day. The 5% trigger (t=0) is the first trade in the day where the stock trades at or above an absolute 5% daily return from the previous day's closing price. Column 1's dependent variable is the raw change in the number of retail sale trades from the hour before the 5% trigger to the hour after the 5% trigger. Column 2's dependent variable is the percentage change of the same measure. *Positive* = 1 for the observations with +5% triggers; *Positive* = 0 for the observations with -5% triggers. All variables are defined in Appendix C. Robust t-statistics are in parentheses. Standard errors are clustered by firm. Statistical significance is denoted by *** p<0.01, ** p<0.05, * p<0.1.

Table 5- Does Fast-Thinking Attention Exacerbate the Disposition Effect?

	(1)	(2)	(3)	(4)
DEPVAR=	*ChRetailSales*	*PctChRetailSales*	*ChRetailSales*	*PctChRetailSales*
Positive	1.402***	0.180***	4.668***	0.318***
	(9.450)	(13.362)	(4.315)	(5.449)
HighRH	-0.546**	-0.108***	1.886***	-0.014
	(-2.149)	(-7.606)	(4.313)	(-0.585)
Positive ×*HighRH*	5.510***	0.244***	2.174**	0.113*
	(15.657)	(11.327)	(1.999)	(1.869)
Lockdown	-1.614***	-0.159***	-2.806***	-0.184***
	(-3.937)	(-5.995)	(-4.323)	(-4.486)
AbsReturn1Hr	237.122***	12.080***	246.588***	13.501***
	(26.899)	(30.582)	(17.079)	(14.841)
Positive×*AbsReturn1Hr*	37.293***	3.893***	117.718***	7.154***
	(4.162)	(6.600)	(2.783)	(3.682)
AbsReturnPastHour	51.294***	5.090***	62.121***	6.998***
	(9.852)	(18.204)	(6.378)	(15.373)
LogAssets	0.061	-0.089***		
	(0.838)	(-23.341)		
AvgRetailVol6Mo	18.468***	-0.005		
	(17.407)	(-0.238)		
LogBTM	-0.849***	0.046***		
	(-5.097)	(4.318)		
Constant	0.792	0.976***	1.727	0.366***
	(0.735)	(17.564)	(1.030)	(4.573)
Observations	169,161	169,161	169,161	169,161
Industry FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Entropy Balanced	No	No	Yes	Yes
Adjusted R-squared	0.0810	0.0453	0.0606	0.0504

Notes: Table 5 presents the results of the estimation of Equation 2, which shows how a high number of Robinhood users receiving push notifications (i.e., high fast-thinking attention) affects the tendency for retail investors to make more sale trades after a positive 5% price change compared to a negative 5% price change (i.e., the disposition effect). The sample includes all firms traded on Robinhood (included in the Robintrack data) over the period May 2, 2018, to August 13, 2020, where the 5% trigger occurs between 10:35 AM ET and 2:55 PM ET to ensure that each hour measured is during normal market trading hours and removing from measurement the first and last five minutes of the trading day. The 5% trigger (t=0) is the first trade in the day where the stock trades at or above an absolute 5% daily return from the previous day's closing price. Column 1 and 3's dependent variable is the raw change in the number of retail sale trades from the hour before the 5% trigger to the hour after the 5% trigger. Column 2 and 4's dependent variable is the percentage change of the same measure. *Positive* = 1 for the observations with +5% triggers; *Positive* = 0 for the observations with -5% triggers. *HighRH* =1 if the number of Robinhood owners (from Robintrack; as of that morning) divided by the number of shares outstanding (from Compustat; as of the most recent fiscal quarter end) is equal to or greater than the median of that variable, 0 otherwise. The 1st and 2nd columns control for the three determinants of high Robinhood ownership (*LogAssets*, *AvgRetailVol6Mo*, *LogBTM*) by placing those variables in the model as control variables. The 3rd and 4th column entropy balance the sample on those three variables—this approach places weights on the control sample (low Robinhood sample) so that the mean, variance, and skewness of the variables are constant across the sample of high and low Robinhood firms. All variables are defined in Appendix C. Robust t-statistics are in parentheses. Standard errors are clustered by firm. Statistical significance is denoted by *** p<0.01, ** p<0.05, * p<0.1.

Table 6- Second Hour after 5% Trigger

	(1)	(2)	(3)	(4)
DEPVAR=	*ChRetailSales [+2]*	*PctChRetailSales [+2]*	*ChRetailSales [+2]*	*PctChRetailSales [+2]*
Positive	1.117***	0.135***	2.989***	0.211***
	(7.207)	(12.213)	(3.737)	(5.999)
HighRH	-5.583***	-0.138***	-5.457***	-0.079***
	(-16.871)	(-12.070)	(-8.010)	(-3.398)
Positive ×HighRH	3.652***	0.123***	2.248***	0.056
	(12.321)	(7.971)	(2.789)	(1.534)
Lockdown	0.551	-0.014	0.535	0.006
	(1.178)	(-0.600)	(0.662)	(0.194)
AbsReturn1Hr	103.709***	7.081***	127.801***	6.692***
	(15.481)	(24.674)	(6.895)	(7.927)
Positive×AbsReturn1Hr	82.497***	5.671***	117.406***	8.349***
	(10.117)	(12.488)	(4.701)	(6.188)
AbsReturnPastHour	-26.582***	-0.761***	-28.813***	-0.542
	(-5.858)	(-3.680)	(-3.165)	(-1.515)
LogAssets	-1.209***	-0.022***		
	(-12.484)	(-8.328)		
AvgRetailVol6Mo	-37.893***	-0.151***		
	(-25.893)	(-10.898)		
LogBTM	1.546***	0.016**		
	(6.899)	(2.081)		
Constant	4.204***	0.232***	-9.732***	0.057
	(3.276)	(5.496)	(-2.922)	(1.015)
Observations	142,255	142,255	142,255	142,255
Industry FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Entropy Balanced	No	No	Yes	Yes
Adjusted R-squared	0.192	0.0336	0.0417	0.0389

Notes: Table 6 presents the results of the estimation of Equation 2, with two changes—the dependent variables and the sample. Column 1 and 3's dependent variable is the raw change in the number of retail sale trades from the hour before the 5% trigger to the 2nd hour after the 5% trigger. The first hour after the 5% trigger (when retail traders are more likely using fast-thinking attention) is dropped from the measurement of the dependent variables. In the 2nd hour after the 5% trigger, it is less likely that users are using their fast-thinking attention and more likely that they are using their slow-thinking attention. Column 2 and 4's dependent variable is the percentage change of the same measure. The sample includes all firms traded on Robinhood (included in the Robintrack data) over the period May 2, 2018, to August 13, 2020, where the 5% trigger occurs between 10:35 AM ET and 1:55 PM ET to ensure that each hour measured is during normal market trading hours and removing from measurement the first and last five minutes of the trading day. The 5% trigger (t=0) is the first trade in the day where the stock trades at or above an absolute 5% daily return from the previous day's closing price. *Positive* = 1 for the observations with +5% triggers; *Positive* = 0 for the observations with -5% triggers. *HighRH* =1 if the number of Robinhood owners (from Robintrack; as of that morning) divided by the number of shares outstanding (from Compustat; as of the most recent fiscal quarter end) is equal to or greater than the median of that variable, 0 otherwise. The 1st and 2nd columns control for the three determinants of high Robinhood ownership (*LogAssets*, *AvgRetailVol6Mo*, *LogBTM*) by placing those variables in the model as control variables. The 3rd and 4th column entropy balance the sample on those three variables—this approach places weights on the control sample (low Robinhood sample) so that the mean, variance, and skewness of the variables are constant across the sample of high and low Robinhood firms. In each column, the coefficients of the interaction term

(*Positive*×*HighRH*) are all significantly lower than the same coefficients in Table 5 using a seemingly unrelated regressions estimation in Stata (suest). All variables are defined in Appendix C. Robust t-statistics are in parentheses. Standard errors are clustered by firm. Statistical significance is denoted by *** p<0.01, ** p<0.05, * p<0.1.

Table 7- Future Returns of Positive Daily 5% Stocks

VAR=	*BHAR[+1, +7]*	*BHAR[+1, +30]*	*BHAR[+1, +60]*	*BHAR[+1, +90]*	*BHAR[+1, +120]*
N	313697	313536	313380	313208	313073
Mean	0.0018	0.0084	0.0182	0.0228	0.0296
Standard Error	0.0002	0.0005	0.0007	0.0009	0.0010
T-Stat	7.8649	18.65	26.78	26.48	28.64
P-Value	< 0.00	< 0.00	< 0.00	< 0.00	< 0.00

Notes: Table 7 presents the future buy-and-hold returns for the full sample of positive 5% trigger stocks starting the date after the 5% trigger. The sample includes all firms traded on Robinhood (included in the Robintrack data) over the period May 2, 2018, to August 13, 2020, where the stock trades at or above absolute 5% return (relative to the previous day's closing price) at any point during the trading day. The buy-and-hold abnormal return is calculated as the buy-and-hold return starting from the closing price of the trigger day to the closing price of the 7^{th}, 30^{th}, 60^{th}, 90^{th}, or 120^{th} day after the trigger day, minus the size decile return over the same period (data from CRSP "erdport1"). Mean buy-and-hold abnormal return equal to zero is tested with single sample t-tests and t-statistics and p-values are shown.

Table 8- Dropping Observations with Extreme Continuation Returns

Panel A- Raw Change in Retail Sales as Dependent Variable

Drop if *AbsReturn1Hr* >	10%	9%	8%	7%	6%
	(1)	(2)	(3)	(4)	(5)
DEPVAR=			*ChRetailSales*		
Positive	3.722***	3.689***	3.365***	3.148***	2.753***
	(5.664)	(5.848)	(6.188)	(5.780)	(4.744)
HighRH	1.918***	1.604***	1.451***	1.062***	0.551
	(5.109)	(4.284)	(3.912)	(2.747)	(1.369)
Positive ×*HighRH*	2.416***	2.643***	2.768***	2.896***	3.243***
	(3.455)	(3.918)	(4.584)	(4.783)	(5.068)
Lockdown	-2.026***	-1.915***	-2.070***	-1.949***	-2.465***
	(-3.180)	(-2.940)	(-3.128)	(-2.970)	(-3.495)
AbsReturnPastHour	-3.739	-12.605*	-21.508***	-24.864***	-20.861***
	(-0.478)	(-1.775)	(-3.221)	(-3.647)	(-2.894)
Constant	3.100**	3.228**	3.195**	2.542*	0.820
	(2.062)	(2.129)	(2.204)	(1.927)	(0.668)
Observations	167,094	164,161	160,385	152,669	134,566
Industry FE	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes
Entropy Balanced	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.0143	0.0145	0.0139	0.0126	0.0117

Notes: Table 8, Panel A presents the results of the estimation of Equation 2 (Table 5) after dropping observations where the return at the end of the one-hour post-5% trigger measurement window is above absolute 10%, 9%, 8%, 7%, and 6% in columns 1-5. The sample includes all firms traded on Robinhood (included in the Robintrack data) over the period May 2, 2018, to August 13, 2020, where the 5% trigger occurs between 10:35 AM ET and 2:55 PM ET to ensure that each hour measured is during normal market trading hours and removing from measurement the first and last five minutes of the trading day. The 5% trigger (t=0) is the first trade in the day where the stock trades at or above an absolute 5% daily return from the previous day's closing price. The dependent variable is the raw change in the number of retail sale trades from the hour before the 5% trigger to the hour after the 5% trigger. *Positive* = 1 for the observations with +5% triggers; *Positive* = 0 for the observations with -5% triggers. *HighRH* =1 if the number of Robinhood owners (from Robintrack; as of that morning) divided by the number of shares outstanding (from Compustat; as of the most recent fiscal quarter end) is equal to or greater than the median of that variable, 0 otherwise. Each column entropy balances the sample on the three determinants of high Robinhood ownership (*LogAssets*, *AvgRetailVol6Mo*, *LogBTM*) by placing weights on the control sample (low Robinhood sample) so that the mean, variance, and skewness of the variables are constant across the sample of high and low Robinhood firms. All variables are defined in Appendix C. Robust t-statistics are in parentheses. Standard errors are clustered by firm. Statistical significance is denoted by *** p<0.01, ** p<0.05, * p<0.1.

Table 8, continued

Panel B- Percentage Change in Retail Sales as Dependent Variable

Drop if *AbsReturn1Hr* >	10%	9%	8%	7%	6%
	(1)	(2)	(3)	(4)	(5)
DEPVAR=			*PctChRetailSales*		
Positive	0.244***	0.253***	0.241***	0.239***	0.256***
	(7.711)	(7.977)	(7.449)	(6.920)	(6.737)
HighRH	-0.013	-0.022	-0.027	-0.029	-0.018
	(-0.607)	(-1.028)	(-1.255)	(-1.360)	(-0.802)
Positive ×*HighRH*	0.125***	0.124***	0.119***	0.113***	0.093**
	(3.556)	(3.517)	(3.356)	(3.020)	(2.285)
Lockdown	-0.136***	-0.132***	-0.137***	-0.105***	-0.109***
	(-3.546)	(-3.407)	(-3.866)	(-2.791)	(-2.771)
AbsReturnPastHour	3.285***	2.881***	2.573***	2.424***	2.625***
	(7.754)	(6.756)	(6.074)	(5.561)	(6.089)
Constant	0.470***	0.445***	0.460***	0.441***	0.351***
	(6.179)	(6.408)	(6.385)	(6.109)	(4.871)
Observations	167,094	164,161	160,385	152,669	134,566
Industry FE	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes
Entropy Balanced	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.0123	0.0127	0.0122	0.0120	0.0119

Notes: Table 8, Panel B presents the results of the estimation of Equation 2 (Table 5) after dropping observations where the return at the end of the one-hour post-5% trigger measurement window is above absolute 10%, 9%, 8%, 7%, and 6% in columns 1-5. The sample includes all firms traded on Robinhood (included in the Robintrack data) over the period May 2, 2018, to August 13, 2020, where the 5% trigger occurs between 10:35 AM ET and 2:55 PM ET to ensure that each hour measured is during normal market trading hours and removing from measurement the first and last five minutes of the trading day. The 5% trigger (t=0) is the first trade in the day where the stock trades at or above an absolute 5% daily return from the previous day's closing price. The dependent variable is the percentage change in the number of retail sale trades from the hour before the 5% trigger to the hour after the 5% trigger. *Positive* = 1 for the observations with +5% triggers; *Positive* = 0 for the observations with -5% triggers. *HighRH* =1 if the number of Robinhood owners (from Robintrack; as of that morning) divided by the number of shares outstanding (from Compustat; as of the most recent fiscal quarter end) is equal to or greater than the median of that variable, 0 otherwise. Each column entropy balances the sample on the three determinants of high Robinhood ownership (*LogAssets*, *AvgRetailVol6Mo*, *LogBTM*) by placing weights on the control sample (low Robinhood sample) so that the mean, variance, and skewness of the variables are constant across the sample of high and low Robinhood firms. All variables are defined in Appendix C. Robust t-statistics are in parentheses. Standard errors are clustered by firm. Statistical significance is denoted by *** p<0.01, ** p<0.05, * p<0.1.

Table 9- Robinhood Outages Placebo Test

VARIABLES	(1) *ChRetailSales*	(2) *PctChRetailSales*
Positive	3.754	-0.049
	(1.108)	(-0.183)
HighRH	0.645	-0.246
	(0.238)	(-1.044)
Positive×HighRH	-2.449	0.198
	(-0.578)	(0.644)
Lockdown	10.792**	0.590*
	(2.338)	(1.827)
AbsReturn1Hr	171.282**	11.145
	(2.029)	(1.588)
Positive×AbsReturn1Hr	168.381	1.246
	(1.478)	(0.158)
AbsReturnPastHour	95.813*	15.170***
	(1.936)	(3.445)
Constant	-7.534**	-0.294
	(-2.035)	(-0.705)
Observations	1,161	1,161
Industry FE	Yes	Yes
Year-Quarter FE	Yes	Yes
Entropy Balanced	Yes	Yes
Adjusted R-squared	0.197	0.119

Notes: Table 9 presents the results of the estimation of Equation 2 for the sample of 5% triggers that occur during Robinhood outages (see Friedman and Zeng 2021, Appendix B). The sample includes all firms traded on Robinhood (included in the Robintrack data) over the period May 2, 2018, to August 13, 2020, where the 5% trigger occurs between 10:35 AM ET and 2:55 PM ET to ensure that each hour measured is during normal market trading hours and removing from measurement the first and last five minutes of the trading day. The sample is further limited by the Robinhood outages compiled by Friedman and Zeng (2021), which includes begin and end times of Robinhood outages where investors were not able to trade or there was a system-wide outage. Friedman and Zeng note seven outages during my sample period, whereas two of the outages occur during the first hour of the trading day and are therefore already excluded from my sample. The five remaining Robinhood outages included in this test are: Oct 17, 2019, 2:33 PM ET – Oct 17, 2019, 2:54 PM ET; Nov 6, 2019, 9:43 AM ET – Nov 6, 2019, 12:54 PM ET; March 2, 2020, 9:38 AM ET – March 3, 2020, 2:13 AM ET; March 3, 2020, 10:04 AM ET – March 3, 2020, 11:55 AM ET; June 18, 2020, 11:39 AM ET – June 18, 2020, 1:08 PM ET. The 5% trigger (t=0) is the first trade in the day where the stock trades at or above an absolute 5% daily return from the previous day's closing price. Column 1's dependent variable is the raw change in the number of retail sale trades from the hour before the 5% trigger to the hour after the 5% trigger. Column 2's dependent variable is the percentage change of the same measure. *Positive* = 1 for the observations with +5% triggers; *Positive* = 0 for the observations with -5% triggers. *HighRH* =1 if the number of Robinhood owners (from Robintrack; as of that morning) divided by the number of shares outstanding (from Compustat; as of the most recent fiscal quarter end) is equal to or greater than the median of that variable, 0 otherwise. Each column entropy balances the sample on the three determinants of high Robinhood ownership (*LogAssets*, *AvgRetailVol6Mo*, *LogBTM*) by placing weights on the control sample (low Robinhood sample) so that the mean, variance, and skewness of the variables are constant across the sample of high and low Robinhood firms. All variables are defined in Appendix C. Robust t-statistics are in parentheses. Standard errors are clustered by firm. Statistical significance is denoted by *** p<0.01, ** p<0.05, * p<0.1.

Table 10- Firm Fixed Effects Sample: Pre and Post Robinhood's Introduction of the Push Notification

	(1)	(2)	(3)	(4)
DEPVAR=	*ChRetailSales*	*PctChRetailSales*	*ChRetailSales*	*PctChRetailSales*
Post	0.888	0.090	-1.591	0.012
	(0.791)	(1.261)	(-1.411)	(0.173)
Positive	8.394***	0.533***	5.432***	0.439***
	(13.205)	(20.070)	(8.103)	(10.738)
Post × *Positive*			4.694***	0.148***
			(4.692)	(3.095)
AbsReturn1Hr	404.990***	16.588***	400.914***	16.459***
	(15.781)	(20.814)	(15.541)	(20.619)
Positive×*AbsReturn1Hr*	93.165***	9.100***	99.112***	9.287***
	(3.210)	(7.415)	(3.361)	(7.542)
AvgRetailVol6Mo	0.000***	0.000	0.000***	0.000
	(6.309)	(1.478)	(6.328)	(1.488)
Constant	1.014	0.601***	2.573***	0.651***
	(1.037)	(10.441)	(2.705)	(11.224)
Observations	82,377	82,377	82,377	82,377
Year-Quarter FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Adjusted R-squared	0.0553	0.0517	0.0559	0.0519

Notes: Table 10 present the results of tests of my hypothesis in the alternative firm fixed effects pre- and post-Robinhood notification sample. According to Robinhood's blog, the application introduced push notifications in February 2016 (Robinhood 2016). This sample includes all stocks with above 75th percentile average Robinhood owners divided by shares outstanding in the Robintrack sample period (2018-2020). The sample includes all 5% triggers for these firms in 2014-2015 (pre-notifications) and 2018-2019 (post-notifications). 2016 and 2017 are omitted to let enough Robinhood users adopt push notifications to document an effect. Column 1 and 3's dependent variable is the raw change in the number of retail sale trades from the hour before the 5% trigger to the hour after the 5% trigger. Column 2 and 4's dependent variable is the percentage change of the same measure. *Post* =1 for observations after 2016, and 0 otherwise. *Positive* = 1 for the observations with +5% triggers; *Positive* = 0 for the observations with -5% triggers. The first two columns do not include the interaction of *Post* and *Positive* (analogous to Table 4 showing the disposition effect on average); columns 3 and 4 include the interaction (analogous to Table 5 showing how fast-thinking attention exacerbates the disposition effect). All variables are defined in Appendix C. Robust t-statistics are in parentheses. Standard errors are clustered by firm. Statistical significance is denoted by *** p<0.01, ** p<0.05, * p<0.1.