Are Individual Investors Tax Savvy? Revaluating Individual Investors Using Robinhood Data

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Abstract: Over two decades ago, Barber and Odean (2004) provided evidence that retail investors are tax savvy. However, retail investing has dramatically changed since then. Using data on individual investor holdings on the Robinhood trading app, we revisit their research question by asking if Robinhood investors efficiently incorporate taxes into their investment decisions. Specifically, we examine asset allocation decisions, tax loss harvesting, and capital gains lock-in effects. Our results suggest that Robinhood investors do not avoid dividend income in their taxable trading accounts, and they even appear to be drawn to high dividend yield equities before the ex-dividend date. Additionally, we see no evidence of tax loss harvesting in December, an event often credited as the mechanism for the "turn-of-the-year" effect, as well as no evidence of tax-induced behaviors following herding events (i.e., strategic sales among stocks with gains after being held for longer than one year). We conclude that Robinhood investors do not appear to be tax savvy.

Keywords: Robinhood; Retail Investors; Taxation, Asset Pricing

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1. Introduction

Whether individual investors understand and internalize income taxes in their investment decisions has long been an empirical question of interest (Hall and Jorgenson 1967; Miller 1977; Scholes and Wolfson 1992). Major advances in the tax literature occurred approximately 20 years ago when Grinblatt and Keloharju (2000) and Barber and Odean (2004) (among others) examined microdata on equity holdings for individual investors.[1] The later study broadly concludes that "tax considerations leave clear footprints in the data" (p. 441), suggesting that the investors from the prior studies (mostly in the late 1990s) had a sense of tax savviness in their decisions. However, the retail trading landscape observed in earlier studies bears little resemblance to today's environment, shaped by advancements like social media, smartphones, and other technology that might alter individual investment activity. With these advances emerges a relatively understudied set of retail investors that primarily trade using applications on their mobile devices. In this study, we revisit the question of whether and to what extent taxes alter retail trading among this new class of modern investors. Using data provided by Robinhood (RH), we fail to find evidence that taxes play a first-order role in their investment decision making. We conclude that tax savvyness does not generalize uniformly across today's investor base.

RH investors gained notoriety with the "meme" stock craze starting in 2020 and may have an outsized influence on market prices due to their penchant for trading. Barber, Huang, Odean, and Schwarz (2022) note that Robinhood users trade three times more per day than E*TRADE users (4.3m versus 1.1m per day). Prior literature documents that individuals engage in tax-motivated trading to take advantage of attributes associated with the security (i.e., whether a company pays dividends, Michaely and Vila 1995) or the timing of the trade (i.e., harvesting tax

[1] We use the term retail and individual investors interchangeably.

losses at the end of the year, Ivkovic, Poterba, and Weisbenner 2005). The broad conclusion drawn from the prior literature is that individual investors know the tax consequences of their equity purchases and sales and that tax rules play a significant role in those trading decisions. Given the impact of RH investors on market prices due to their proclivity for intraday trading, it is important to determine how well prior findings generalize to this group.

We propose there are at least three reasons why prior inferences may not generalize to RH investors. First, companies like RH have changed the individual investment environment by introducing easy to execute trading via mobile apps, and these trades can occur during normal and extended hours.[2] The investors examined in Barber and Odean (2002; 2004) traded using a brokerage account that, like most other platforms in the 1990s, charged a fee to execute a trade. Individuals no longer need investment advisors or brokerages to execute their trades, and RH does not charge users. Instead, RH users can buy and sell shares in a company with a few taps of their mobile devices, a technology that was not even conceivable when the prior studies formed their conclusions. Some individuals even view investing in stocks as akin to betting on sporting events, as they both reflect a form of legalized gambling that can now be executed with relative ease (Banerji 2024; Wang 2024).

Second, the taxation on equity income is not static, and there have been several major shifts, starting with a series of Bush-era tax cuts in the early 2000s through major tax reform with the TCJA in 2017. In the U.S., individuals pay taxes on income from their equity investments via dividend income and capital gains when the stock is sold at a gain. Additionally, the tax code introduces nuances that influence whether and to what extent sales of or income from equity investments are taxed, such as preferential tax rates for equity investments held for more than one

[2] RH allows users to track and trade stocks outside of traditional market hours via either extended-hours trading or the 24 Hour Market (see https://robinhood.com/us/en/support/articles/24hour-market/).

year (i.e., long-term capital gains tax rates), tax-deferred accounts (i.e., retirement accounts and health savings accounts), and tax-exempt investments (i.e., municipal bonds). These tax provisions create incentives based on the taxability of the investor, such as netting taxable gains and losses (Erickson, Hanlon, Maydew, and Shevlin 2020). Compared to investors from the late 1980s through the early 2000s, low income RH investors are more lightly taxed, 10% vs. 15%, on equity income, and there are now preferential tax rates on certain dividend income (i.e., qualified dividends). Accordingly, the tax effects could be muted compared to prior time periods. While it is possible that some RH users do not have any other forms of taxable income, based on an average trading account value of $1,000 to $5,000, it seems reasonable that many, if not most, of these investors are generating other forms of taxable income that require them to pay taxes on investment income (Salzman 2020).

Third, RH caters to a new breed of investors. These investors represent a segment of the market that wasn't (or represented a much smaller percentage of the sample) present in prior studies that rely on data from more traditional brokerage houses. Welch (2022) shows that investors using RH tend to have different trading patterns than more sophisticated investors as they buy bigger name stocks with higher previous trading volume. He also conjectures that these investors are significantly less likely to base their trades on traditional sources of financial information and outlooks (i.e., analysts' reports, earnings announcements, and financial statements) and, instead, are more willing to turn to alternative channels like Reddit, YouTube, and TikTok. Similarly, Barber et al. (2022) state that: "Robinhood users are more likely to trade speculatively. As a result, a smaller proportion of their trading is motivated by nonspeculative objectives such as saving for retirement, meeting liquidity needs, harvesting tax losses, or rebalancing their portfolio" (emphasis added, p. 3143). As these investors are choosing their investments off of non-traditional

considerations, we expect factors like the tax implications of their trades to be significantly less important or not considered at all.

Based on the above arguments, we suggest that prior studies do not necessarily generalize to RH users. Given the importance of RH as a major trading platform that has the power to move market prices, it is important that we fully understand whether the conclusion that individual investors understand and incorporate taxes into their investment decisions holds among this new breed of investors in this current era of technology and investing. Accordingly, we revisit the research question from Barber and Odean (2004): are individual investors tax savvy?

We use a specialized data set provided by Robintrack.net (RT) to assess our research question. RT downloaded data on the total number of investors holding a position in a security on the RH platform. Using an approximately hourly script, RT made this RH data on intraday holdings public between March 2018 and August 2020. While there is some noise in this data, such as dual class stocks with .A or .B appeared to be missed in an early version of the RT download (Welch 2022), it provides over 10 million observations from a unique set of retail investors.[3] Despite its limitations, this dataset provides an unparalleled look into retail investors in the late 2010s and early 2020s, on which numerous prior and concurrent studies are already capitalizing (e.g., Moss, Naughton, and Wang 2024).

We assess the tax savviness of individual investors across several tests using a RT sample of 1,456,233 daily stock observations. First, we descriptively assess whether these individual investors are holding dividend-paying stocks. We do this by examining the prevalence of dividend-

[3] One noteworthy drawback to this data is that it does not provide each investor's trading accounting. Instead, RT reports the number of unique RH traders who own at least one share of a particular security at a given point in time. Despite this limitation, as compared to some more traditional brokerage houses or higher wealth investors, we believe many of the RH traders do not hold much, perhaps other than retirement savings, outside of this platform, reducing concerns that we cannot witness the full scope of trading activity.

paying stocks among RH investors. Bergstresser and Poterba (2004) discuss that holding dividend-paying stocks in tax-deferred accounts and growth stocks in taxable accounts are tax-efficient undertakings. Assuming that most RH traders are taxable investors, we expect that, all else equal, the RH investors should prefer to hold a portfolio with relatively few dividend-paying stocks.[4] Second, we examine RH investors' holdings changes around the ex-dividend day, allowing us to capture tax heterogeneity among RH users (Dhaliwal and Li 2006). As suggested by Michaely and Vila (1995; 1996), investors should make tax-motivated trades around the ex-dividend days due to their tax preferences in that the tax-disadvantaged portion of returns should be prioritized more by institutional investors over individual investors due to their tax consequences.

Third, we examine tax loss harvesting. Many view tax loss harvesting as the underlying mechanism driving the "turn-of-the-year" or "January effect." This stock price anomaly consists of abnormally low returns in December and abnormally high returns in early January among small capitalization stocks (e.g., Sias and Starks 1997; Poterba and Weisbenner 2001; Grinblatt and Moskowitz 2004; Sikes 2014). This price change is attributed to individual investors selling poorly performing stocks before the end of the year to "harvest" the tax loss for the current taxable year. This tax-induced selling, which can be seen as optimal from a tax perspective, creates a temporary reduction in stock prices that reverses in the early part of January. Consequently, we would expect tax-savvy investors to engage in the selling of loss-generating stocks in December.

Finally, we test for evidence of capital gains lock-in following herding events. Prior research hypothesizes and finds evidence that a preferential tax rate on equities held for over a designated period (typically 12 months) alters trading patterns such that investors are less willing to sell appreciated assets prior to qualifying for this lower rate (Dai, Maydew, Shackelford, and

[4] Despite this assertion, we cannot completely rule out that many RH users are lightly taxed, and this is simply a clientele effect. Accordingly, this first analysis cannot be viewed in isolation and is simply one piece of the puzzle.

Zhang 2008). Thus, capital gains rates "lock-in" an investor into holding a recently purchased asset (e.g., Dai et al. 2008). Specifically, we examine trading one year after a herding event for stocks with capital gains. Tax-savvy investors should be inclined to sell their positions after the one-year mark in order to obtain long-term capital gains preferential tax rates.

We fail to find evidence of taxes guiding RH users across all analyses. In particular, we find that RH users own significant amounts of dividend-paying stocks and hold these stocks leading up to the ex-dividend day. In fact, we see little change in shareholder ownership in the days leading up to the ex-dividend day. The only ownership change we note is an increase in the ownership of high-dividend yield stocks from four days through the ex-dividend date. This increase is the opposite of typical tax-efficient theories, as it appears RH users seek out dividend income. These shareholders then divest those dividend-paying equities shortly afterward. One possibility is that we are capturing a dividend clientele effect (Graham and Kumar 2006), where RH investors, on average, face no taxation on their dividend income. While this is an appealing alternative explanation as clientele effects are difficult to quantify empirically, this is likely not occurring due to the increase in holdings before the ex-dividend date that reverses afterward. These changes in ownership make it unlikely that the dividend payments are eligible for "qualified dividend" treatment and instead are most likely subject to normal income tax rates. Thus, in 2019, even low-income investors are subject to a 12% marginal tax rate.

In addition to the dividend analysis, we fail to find evidence of any changes in ownership of poor-performing stocks among RH users around the turn of the year. Using a host of regression specifications, we fail to see evidence of tax-induced trading, suggesting that these investors are not taking advantage of tax loss selling at the end of the calendar year. One explanation for this lack of a finding is simple: they take the *other side* of the trade from more sophisticated investors

(i.e., for every buyer, there must be a seller). Combining these three analyses, we conclude that individual investors' previously documented tax savviness may not carry over to current individual investors using RH.

Lastly, we find no evidence of RH investors selling their holdings one year after purchasing. Specifically, we identify events in which a large number of investors purchase a stock and do not find that a similarly large number of investors sell the stock a year later when the gain on the sale qualifies for long-term capital gains tax rates. Our results similarly suggest that RH investors are not making tax efficient investment decisions on average.

Our results contribute to the literature on how individuals integrate taxation into their equity investment decisions. While studies show that individual investors consider and prioritize taxes in their equity trading decisions (Barber and Odean 2004; Jin and Kothari 2008), prior studies have based this evidence on trades conducted before the popularization of mobile trading applications. In fact, much of the evidence derives from data generated during the infancy of Internet trading, which is now the primary vehicle for buying and selling shares in a company. Equity investments have long been perceived as gambling only for the wealthy due to the need to access brokerages to execute the trades (Wealth 2022). Apps like RH significantly altered this game by putting the trades in the hands of any potential investor with a smartphone and a bank account. Whether prior literature's inferences continue to hold among a fundamentally different group of investors is important to understand, given that the radical shift of investor composition appears to be permanent.[5]

Our analysis contributes to the tax and asset pricing literature. A significant portion of knowledge about retail investors is drawn from 1990s data (e.g., Grinblatt and Keloharju 2000).

[5] For example, according to RH's financial statements, their funded customers has grown from 12.5 million in 2021 to 23.4 million in 2023.

While theoretical literature suggests that individual investors, in general, are better off locating taxable assets in tax-deferred accounts (e.g., Dammon, Spatt, and Zhang 2004), we see evidence to the contrary. We caveat that we do not have the full portfolio of assets per investor. However, Welch (2022) suggests that the RH data broadly represents retail investors. Additionally, while prior literature documents the turn-of-the-year effect in several settings (e.g., Starks, Yong, and Zheng 2006), we fail to find strong evidence of tax loss harvesting. Overall, we present robust evidence that RH investors are indeed a "new breed" of investors and that prior literature's findings on tax savviness do not appear to generalize to RH users.

2. Background Literature

2.1 Taxes and Investing

Taxes are a critical friction for household personal finances, particularly investment decisions. While there is a mature stream of literature on the association of taxes and capital market transactions, the literature on the behavior of retail investors is relatively unexplored. Much of what we know about retail investors comes from studies that used 1990s data. These include Grinnblatt and Keloharju (2000), who utilize the Finnish Central Securities Depository dataset, which covers the investment positions of Finland's population, and Bergstresser and Poterba (2004), who rely on the Survey of Consumer Finance to map out asset allocation decisions for a large cross-section of U.S. households. Barber and Odean (2004) are most similar to us, who use data from a retail brokerage house to determine how taxes influence retail investors. They conclude, "Though tax considerations leave clear footprints in the data we analyze, many households could improve their after-tax performance by fully exploiting the tax avoidance strategies available on equities." (pg. 441). For tractability, we focus our remaining discussion on three mechanisms through which investor-level taxes may influence the investing decisions of

individual Robinhood investors: (1) which stocks to own, (2) the timing of taxable sales, and (3) how long to own to specific stocks. For a recent survey of the literature on household personal finance decisions, see Gomes, Haliassos, and Ramadorai (2021).

Generally speaking, investors are better off holding non-dividend-paying equity investments in taxable accounts. Concurrently, investors tend to be more tax-efficient when holding bonds and dividend-paying equities in non-taxable accounts (e.g., 401k, IRA, etc.). This asset location decision allows investors to shield themselves from taxable income by allowing taxable accumulations to grow tax-deferred. While theoretically simple, there is extensive literature on optimal asset placement locations (e.g., Dammon et al. 2004; Fischer and Gallmeyer 2017). Additionally, investors face a progressive marginal tax rate, creating "clientele" effects. Research on these clientele effects presents evidence of an endogenous sorting where investors who are more lightly taxed on their income have a higher demand for investment vehicles that generate taxable gains (e.g., Graham and Kumar 2006). There is also some evidence that managers at these investments "cater" to their clientele base (e.g., Sialm and Starks 2012).

Next, taxes play a critical role in the timing of trades. One phenomenon seen across many different investment types (e.g., Starks et al. 2006; Sikes 2014) is increased tax loss harvesting around the end of the calendar year. Often called either the January effect or the turn-of-the-year effect, investors sell investments with taxable losses towards the end of the year to offset other gains the investor may have. This increase in selling activity puts downward price pressure on these investments in December, reversing in January when there is no longer an incentive to crystalize taxable losses.

The last effect we discuss is the capital gains lock-in effect (Ivkovic et al. 2005; Dai et al. 2008). Investors reduce the tax on certain capital assets if they hold the assets for a certain period,

assuming that long-term investment ownership should be incentivized as a means for individuals to accumulate wealth. The typical holding period to qualify for this preferential capital gains rate has changed over time, but for much of the recent past, it has been at least 12 months. This difference in tax rates can be substantial. In 2019, the top long-term capital gains tax rate was 20%, whereas the top tax rate on short-term capital gains was 37%—a difference of 17%. This discontinuity at 12 months creates a tax incentive for retail investors to hold onto investments for at least a year (i.e., "locking in" one's position).

We caveat this discussion by acknowledging that there are many non-tax reasons to own a specific stock. In fact, an investor who can purchase a tax-advantaged stock that is losing money versus a non-tax-advantaged stock that is making money will typically be better off choosing the latter. However, given the numerous different stocks that investors can choose, we assume that investors are often faced with the choice between two similarly performing stocks that vary across tax attributes (i.e., whether the stock pays dividends, the timing of the stock purchase, or whether the stock has been held for a year). Consequently, we expect that tax-savvy investors can make equity investment decisions that reflect their tax knowledge.

2.2 Robinhood

Brokerage accounts have changed drastically over the past 50 years. Where one once called a broker to place an order by phone, now many people trade on their computer or a mobile application on a smartphone. Additionally, now, many brokerage houses charge no fee for many trades. Robinhood is an online brokerage house that caters to a new breed of investors. RH investors gained notoriety with the "meme" stock craze starting in 2020. This group, often following Reddit investment blogs, targeted companies with large institutional short positions as a means of creating significant losses for many hedge funds. Welch (2022) suggests that " this

"crazy mob" narrative is misleading. The typical RH investments were much saner" (pg. 1491) and that RH investment portfolios are a reasonable proxy for retail investors more broadly. In addition to nonconventional trading strategies, RH investors may have an outsized influence on market prices due to their penchant for trading. Barber et al. (2022) state that: "In June 2020, Robinhood users averaged 4.3 million revenue trades per day (Daily Average Revenue Trades or DARTs), more than E*TRADE at 1.1 million, TD Ameritrade at 3.8 million, Charles Schwab at 1.8 million, Interactive Brokers at 1.9 million, or Fidelity at 1.4 million. Thus, Robinhood users accounted for roughly 30% of daily trades from the largest brokerage firms catering to retail investors and have the potential to move prices." (p. 3145).

What we know about how taxes influence investment decisions may not generalize to the RH data for several reasons. First, RH users are generally younger and less wealthy than the average retail investor. This notoriety is, by design, where RH advertises as "Join a new generation of investors," and their webpage has an "investing 101" section that outlines what an investment, stock, and the stock market is. This advertising differs from Charles Schwab's "Insights & Education" page, which lists a discussion of high-yield bonds and the Fed at Jackson Hole.[6]

One concern voiced by those in the popular press as well as legislators is that RH acts as a "game" and may encourage gambling-like trading behavior. Part of this concern is due to the trading platform, which is an app that allows users to trade without commissions. Moreover, while investors often view long-term holdings of equity investments as one means to build generational wealth, frequent short-term trading by relative novices may result in losses among a group of investors who are the least able to recover from the economic loss. Barber et al. (2022) and Welch (2022) provide evidence that these fears are not unfounded.

[6] Based on their website as of August 28, 2024.

Lastly, other studies outside of tax examine the behavior of RH investors to determine if the inferences from prior literature generalize to this setting. This analysis is particularly important given the penchant of RH users to trade frequently, thus moving market prices. One example is Moss, Naughton, and Wang (2024). These authors show that RH users respond to earnings information and adjust their holdings. However, they do not respond to environmental, social, and governance (ESG) disclosures.

3. Research Design

3.1 Robintrack Data

We obtain Robinhood data from Robintrack (RT), which began collecting data in May 2018 and ceased collection on August 13th, 2020. RT reports the number of unique users that own a particular stock at a given date and time. While this data is updated approximately hourly, we only keep the last observation daily such that we have one observation per company per day. Additionally, several Robinhood outages or other issues result in holes in the data. Despite some limitations, this data has been used by many researchers (see Barber et al. 2022 and Welch 2022) and is one of the largest databases of recent retail investor activity.

3.2. Sample Selection

We first derive our sample from the CRSP and Compustat quarterly files, matching the sample period to the dates for which data is available through RT. RT ran scripts to download the data made available by Robinhood through their public API beginning in 2018 and ending in 2020 due to the discontinuation of the API by Robinhood. Therefore, our beginning sample consists of 2,555,574 ticker-day observations with data available in CRSP and Compustat from June 1, 2018,

to August 13, 2020.[7] These observations correspond to 5,336 unique firms and 555 valid trading days.

To further refine our initial sample, we remove observations that switch share codes during the sample period and retain only observations classified as ordinary equity (CRSP share codes 10 and 11), thus removing observations classified as REITs or incorporated outside of the United States. Next, Welch (2022) finds that RT incorrectly reports observations for firms with multiple share classes. Thus, we remove observations for firms with multiple classes of shares. Third, to classify firms from the CRSP/Compustat universe as "Robinhood" firms, we require a pseudo-balanced panel in which a firm must have at least one observation per quarter of our sample period to be classified as a "Robinhood" firm. Finally, we remove observations without data to calculate the number of investors and returns for December and January. Our final sample consists of 1,456,233 ticker-day observations in RH, corresponding to 2,748 unique firms. Table 1 presents the sample selection for our analyses.

[Insert Table 1 Here]

3.3 Research Design

3.3.1 Asset Allocation Analysis

In our first analysis, we ask the simple question of whether and to what extent individual investors are holding dividend-paying stocks. Most shareholders face a tax liability on their dividends received, which is either 15% at standard levels or 20% if their adjusted gross income exceeds $518,901.[8] While dividends represent income to firms' shareholders, they also create

[7] We note that Robintrack began collecting data on May 18, 2018. However, Moss et al. (2024) finds that the data in May is sparsely populated. Therefore, we follow both Moss et al. (2024) and Welch (2022) and begin our sample in June.

[8] This value is for 2024 taxpayers filing as single. Furthermore, single taxpayers in 2024 earning less than $47,025 face no taxes on their dividend income. However, the number of individuals owning stock in this group is very small, and they are unlikely to be represented frequently in our sample (see https://www.statista.com/chart/30224/share-of-americans-who-own-stock/).

taxable income, accelerating the taxes investors owe on the firm's investment. In contrast, if firms hold and reinvest that cash, the shareholders can conceivably continue to realize value increases, deferring their tax liability until the gain is recognized. Put differently, the shareholders will defer paying taxes indefinitely and only once the investors sell the shares. In an extreme situation, shareholders can infinitely lower their tax liability on unrealized gains by holding their shares until death. Their descendants often then inherit the shares received with a tax basis of the current fair market value (rather than the initial purchase price). Regardless of when or how the shares are ultimately disposed of, holding dividend-paying stocks is tax-inefficient for most individual investors (Bergstresser and Poterba 2004).

To perform our analysis, we use the descriptive data of our combined data set to examine whether RH investors own dividend-paying stocks and how likely they are to choose them. If the investors act tax-efficiently, we expect them to own only non-dividend-paying stocks. While it may be unreasonable for investors to own no dividend-paying stocks, an alternative explanation is that they own relatively few dividend-paying stocks and, instead, focus their investments on stocks that do not pay dividends. We primarily examine these tests using univariate tests.

3.3.2 Ex-Dividend Day Test

Next, we turn to the stock holdings among RH users surrounding the ex-dividend day. The ex-dividend day is the day before the firm records the dividend, and it determines who is to receive the dividend that the firm ultimately pays. For instance, suppose an investor purchases a stock on 1/1 and sells it on 2/28. If the company pays a dividend on 3/3, then the investor is not an owner of the stock on the dividend pay date. However, if the company has an ex-dividend date of 2/14, then the investor owns the stock at that time, and even though the investor does not own the stock when the firm pays the dividend, the investor is still entitled to the dividend.

Michaely and Vila (1995; 1996) provide evidence that investors acknowledge this ex-dividend day as it significantly distorts their trading activities in line with expected tax preferences. Assuming this is the case, one would expect RH users holding dividend-paying stocks to unload their shares before the ex-dividend date.[9] We test this expectation in two ways. First, we examine the relation between the number of investors owning the shares (*Investors*) and each day surrounding the ex-dividend day as follows:

$$\begin{aligned} Investors_{i,d} = {} & \beta_1 \times T\_pre\_10_{i,d} + \beta_2 \times T\_pre\_9_{i,d} + \beta_3 \times T\_pre\_8_{i,d} + \beta_4 \times T\_pre\_7_{i,d} \\ & + \beta_5 \times T\_pre\_6_{i,d} + \beta_6 \times T\_pre\_5_{i,d} + \beta_7 \times T\_pre\_4_{i,d} + \beta_8 \times T\_pre\_3_{i,d} \\ & + \beta_9 \times T\_pre\_2_{i,d} + \beta_{10} \times T\_pre\_1_{i,d} + \beta_{11} \times T\_0_{i,d} + \beta_{12} \times T\_1_{i,d} + \beta_{13} \times T\_2_{i,d} \\ & + \beta_{14} \times T\_3_{i,d} + \beta_{15} \times T\_4_{i,d} + \beta_{16} \times T\_5_{i,d} + \beta_{17} \times T\_6_{i,d} + \beta_{18} \times T\_7_{i,d} + \beta_{19} \times T\_8_{i,d} \\ & + \beta_{20} \times T\_9_{i,d} + \beta_{21} \times T\_10_{i,d} + \varepsilon_{i,d} \end{aligned} \quad (1)$$

Each independent variable is an indicator variable, taking a value of 1 for that day, and 0 otherwise. We designate the days before the ex-dividend day using a "*T_pre*_X" variable name (where X is the relative day) and all variables on or after the ex-dividend day using a "*T*_X" variable name. In addition to examining the average number of investors, we also examine the change in the number of investors owning a specific stock from the previous day (*Investor_Chg*). We cluster standard errors at the firm level and present results with and without firm fixed effects.

3.3.3 Tax Loss Harvesting

For our third analysis, we examine tax loss harvesting. The theory behind tax loss harvesting is simple. A taxpayer cannot reduce their gains by losses unless they physically sell the stock. This notion has led to a phenomenon often called either the January or turn-of-the-year effect. Investors sell investments with taxable losses towards the end of the year to offset other gains the investor may have. This increase in selling activity puts downward price pressure on these investments in December, reversing in January when there is no longer a strong incentive to

[9] The flip side of this trade are tax-insensitive institutional investors who would be more willing to hold the shares on the ex-dividend day.

crystalize taxable losses. This effect is strongest among small-cap stocks (Sikes 2014), where prices may be more sensitive to lower trading levels.

While we motivate this analysis on the turn-of-the-year effect, we diverge from prior literature that examines price reactions. Instead, the RH data allows us to examine the number of unique investors that hold a particular asset. Accordingly, we analyze the underlying mechanism that causes the turn-of-the-year effect: December tax loss harvesting. For this analysis, we first descriptively examine firms' holdings with cumulative positive and negative returns from February 1 to November 30. We measure returns from February to December to avoid the turn-of-the-year effect altering market prices. If RH investors are harvesting tax losses, we should see a decrease in holdings among equities with negative cumulative returns in the several trading days before year-end. Meanwhile, the turn-of-the-year effect suggests that this downward price pressure results in an uptick in purchases during the first several days of January. We do not make any predictions on the post-year-end activity as it is unclear how taxes might influence January equity trading activities relative to our expectations of how taxes may influence December selling. We formally test tax loss harvesting with the following regression equation:

$$Investors_{i,d} = \alpha + \beta_1 \times December_{,d} + \beta_2 \times NegativeReturn_{,d} + \beta_3 \times December*NegativeReturn_{i,d} + \beta_4 \times January_{i,d} + \beta_5 \times January*NegativeReturn_{i,d} + \mathcal{E}_{i,d} \quad (2)$$

We present this analysis for the raw number of investors and the change in the number of investors. *December* and *January* are indicator variables that take a value of 1 for observations within the last 10 trading days of December and the first 10 trading days of January, respectively. *NegativeReturn* is an indicator variable that takes a value of 1 for observations that have a negative return from February to December. To the extent we see tax loss harvesting, we expect β_3 to be negative and significant. If the turn-of-the-year effect encourages investors to purchase relatively "cheaper" stocks in January, then β_5 will be positive and significant. Similar to our ex-dividend

day analysis, we cluster standard errors at the firm level and present results with and without fixed effects.

3.3.4 Capital Gains Lock-In

In our final analysis, we study the capital gains lock-in effect, which refers to the period of time in which taxpayers are "locked into" capital gains assets to quality for the long-term capital gain tax rate. In the United States, this period has historically been a year or more, meaning that investors who purchase equity must hold their appreciated assets for at least a year before selling if they want the gains taxed at a preferential long-term capital gains rate. Prior literature notes that lock-in effects alter corporate decision making (e.g., M&A activity in Ayers, Lefanowicz, and Robinson (2007); CEO risk taking in Yost (2018)) although recent evidence for individual investors is more scant. We expect that tax-savvy investors will sell after the 12-month mark instead of disposing of appreciated assets early and subjecting the gain to higher tax rates.

Our data does not allow us to see individual brokerage accounts; therefore, we cannot observe if a specific investor divests a stock purchased a year ago. We circumvent this data limitation by instead identifying herding events, days in which an abnormally high volume of investors purchase a stock. By identifying these instances, we are then able to look a year ahead of each event to examine if there is also an abnormal amount of trading activity when the investors who purchased the stock reach the end of their one-year lock-in period. We follow Barber et al. (2022) to identify herding events. Specifically, herding events are defined as stocks with a minimum of 100 users on day $T - 1$ and in the top 0.5% of observations based on *InvestorRatio* on day T. *InvestorRatio* is defined as the number of investors on day T divided by the number of investors on day $T - 1$. Our test of capital gains lock-in is as follows:

$$Investors_{i,d} = \beta_1 \times YearLater\_pre\_10_{i,d} + \beta_2 \times YearLater\_pre\_9_{i,d} + \beta_3 \times YearLater\_pre\_8_{i,d} + \beta_4 \times YearLater\_pre\_7_{i,d} + \beta_5 \times YearLater\_pre\_6_{i,d} + \beta_6 \times YearLater\_pre\_5_{i,d}$$

$$+ \beta_7 \times YearLater\_pre\_4_{i,d} + \beta_8 \times YearLater\_pre\_3_{i,d} + \beta_9 \times YearLater\_pre\_2_{i,d} + \beta_{10} \times YearLater\_pre\_1_{i,d} + \beta_{11} \times YearLater\_0_{i,d} + \beta_{12} \times YearLater\_1_{i,d} + \beta_{13} \times YearLater\_2_{i,d} + \beta_{14} \times YearLater\_3_{i,d} + \beta_{15} \times YearLater\_4_{i,d} + \beta_{16} \times YearLater\_5_{i,d} + \beta_{17} \times YearLater\_6_{i,d} + \beta_{18} \times YearLater\_7_{i,d} + \beta_{19} \times YearLater\_8_{i,d} + \beta_{20} \times YearLater\_9_{i,d} + \beta_{21} \times YearLater\_10_{i,d} + \mathcal{E}_{i,d} \quad (3)$$

Similar to our ex-dividend day analysis, we create indicator variables denoting the trading days surrounding the one-year period after a herding event A "*YearLater_pre_X*" variable name (where X is the relative day) denotes the days before and after the one-year mark (e.g., *YearLater_pre_1* is one year after the herding event), and "*YearLater_X*" variable name denotes days after (e.g., *YearLater_0* is one year and one day after). Because we are interested in trading one year after herding events, we restrict our herding event coding to events that have trading days one year later in our sample. As capital gains lock-in only relates to stock with a gain, we only code indicator variables for stock-days with a gain relative to the stock price on the day of the herding event. Similar to our prior tests, we additionally examine the change in the number of investors owning a specific stock from the previous day (*Investor_Chg*). We cluster standard errors at the firm level and present results with and without firm fixed effects.

4. Results

4.1 Asset Allocation and Ex-Dividend Day Results

We begin our empirical analysis with the descriptive statistics for our two dividend analyses. In Table 2, Panel A, we present summary statistics on the number of investors and dividends among dividend-paying equities, Panel B presents the summary statistics among non-dividend-paying equities, and Panel C presents the comparison to the universe of Compustat and CRSP. It is important to note that our dependent variable for our analysis is at the firm-day level. However, items that do not change daily, namely dividend yields, are measured less frequently

(and have a smaller N). This descriptive data suggests that, on average, RH users own more non-dividend paying stocks (*LogInvestors:* Panel A – Dividend Paying Stocks: Mean 5.515; Panel B – Non-Dividend Paying Stocks: Mean 6.168). Despite the lower ownership, there is no indication that firms avoid dividend-paying equities. To formally test this conjecture, we compare the average RH sample observation to the universe of Compustat and CRSP over the same timeline. We present the t-test in Panel C of Table 2. The variable *RegDivsThisYr* is the total dividend amount per share, and *DivPayerThisYr* is an indicator set to 1 for dividend-paying stocks. RH users, on average, have a value of 0.525 for *RegDivsThisYr*. In comparison, the CRSP/Compustat Universe has an average value of 0.446. Furthermore, the average value of *DivPayerThisYr* is 0.461 among RH users but only 0.408 for the CRSP/Compustat University. Both differences (0.079 and 0.052) are significant at the $p < 0.01$ level. This analysis suggests that RH users favor dividend-paying equities more than the typical CRSP/Compustat securities portfolio might otherwise suggest.[10]

[Insert Table 2 Here]

We next move to the ex-dividend date analysis. While the previous analysis suggests that RH users prefer dividend-paying equities, this allows us to draw stronger inferences by isolating trading around the ex-dividend date. To the extent RH investors are tax savvy, we predict investors will lower their equity holdings in dividend-paying stocks before paying a taxable dividend. In Table 3, Panel A, we present the descriptive statistics for this sample. We see an average increase in investors up to the ex-dividend date. In particular, the mean holdings go from 1,942.562 on day t-10 to 1,961.892 on the ex-dividend day. Furthermore, the median average investors continue to exhibit an increase, albeit less extreme (196 on t-10 to 204 on the ex-dividend date). We also note

[10] We compute these sample statistics based on the entire RH sample and the sample that represents the intersection of Compustat and CRSP daily data. For the RH sample, there are some daily observations that do not have any RH user owners; however we do require that the stock be owned by at least one RH user in every quarter in our sample.

this increase across all sample ranges with an increase in the P25 and P75 quartiles. We plot the average amounts for total users owning a stock and the day-to-day change in Figure 1. This descriptive data indicates that RH investors are not avoiding receipt of taxable dividends, suggesting that RH users are not prioritizing taxes regarding their equity investments.

In Table 3, Panel B, we examine the holdings around the ex-dividend date using both the total of and changes in RH investors. We present our analysis using a regression both without firm fixed effects in columns (1) and (3) and with firm fixed effects in columns (2) and (4). In columns (1) and (2), we see that, on average, fewer RH users own dividend-paying stocks around the ex-dividend date relative to other days throughout the year. We speculate that this could be a byproduct of RH users largely focusing on stocks that have seen recent media attention (Barber et al. 2022) or stocks that have a unique draw to RH users, such as Aurora Cannabis, who Welch (2022) refers to as "experience holdings." However, we note that the coefficient steadily declines over the days. For instance, the coefficient on *T_pre_10* is negative and significant (column (1): coef. = -415.95, $p < 0.05$; column (2): coef. = -217.53, $p < 0.01$). This coefficient continues to be negative and significant up through the ex-dividend date (column (1): coef. = -394.32, $p < 0.05$; column (2): coef. = 191.02, $p < 0.01$).

Focusing on columns (3) and (4), we present the same analysis but using a prior day to current day change, allowing for a more straightforward interpretation of the trend in our coefficients. We see that there is a positive and statistically significant increase in RH holdings on the day before the ex-dividend date (*T_pre_1* column (3): coef = 2.24, $p < 0.01$; column (4): coef. = 1.96, $p < 0.01$), which quickly reverses on the ex-dividend date (column (3): coef. = -1.18, $p < 0.05$; column (4): coef. = -1.44, $p < 0.01$) and the following day (column (3): coef. = -1.57, $p < 0.01$; column (4): coef. = -1.85, $p < 0.01$). The estimates were generally negative and sometimes

statistically significant for the following several days. This result suggests that some RH users purchase stocks to obtain dividends, while another non-mutually exclusive group sells shortly after the ex-dividend date. Due to data limitations, we cannot determine if it is the same RH investors buying and then quickly selling or if these two events are separate.[11] This evidence supports the notion that RH investors do not incorporate income taxes into their equity trading as we would have expected those that do to significantly *decrease* their dividend-paying holdings before the ex-dividend date, followed by an increase in the subsequent days. We see the opposite relation.

[Insert Figure 1 Here]

[Insert Table 3 Here]

One alternative interpretation of our analysis in Table 3 is that investors buy high-performing dividend-paying stock, but these equities pay very low dividends. Thus, they act efficiently even if they are not tax-efficient. To address this potential concern, we split the sample into quintiles and separately examine the low (or no) dividend yield quintile compared to the high dividend yield quintile. If we draw our prior inferences from low-dividend yield stocks, we expect to derive the increase (decrease) in investors just before (just after) the ex-dividend date from the lowest quintile of dividend yield stocks.

To test this, we partition the sample based on the dividend yield (*Div_Yield_All*), which is the absolute value of the dividend divided by the share price on the last cumulative dividend day (following Rantapuska 2008). We then re-perform our regression analysis on both quintiles in columns (1) and (2) for the low dividend yield quintile and columns (3) and (4) for the high

[11] One item of note is the low R^2 of our analysis without fixed effects. Individual investors' trading behaviors are notoriously difficult to model in cross-sectional tests and the explanatory power is often low. Our analyses are in line with prior studies (e.g., Murphy and Stekelberg 2021).

dividend yield quintile.[12] See Table 4. First, compared to the primary specification in Table 3, the point estimates for the ten days around the ex-dividend date in columns (1) and (3) are insignificant. We attribute this insignificance to variation in the sample composition of shareholders across different types of equities. However, we do find in column (3) that the total number of investors coefficient steadily increases from day t-10 (coef. = -164.03) to day t-1 (coef. = -83.39). In columns (2) and (4), we examine the changes in ownership. A unique pattern emerges. In column (2), which examines our low-dividend yield equities, there is a significant decline in RH investors in days t-4 (coef. = -2.64, $p < 0.01$), t-3 (coef. = -1.46, $p < 0.05$) and t-2 (-2.09, $p < 0.01$). Conversely, in column (4), we see a positive and significant coefficient in each day leading up to the ex-dividend date, concluding with a spike in ownership in the day prior (coef. = 9.31, $p < 0.01$) to the ex-dividend date. This pattern ends on the ex-dividend date, suggesting that RH investors are aware of high dividend yields and actively seeking to obtain them. This result differs from the lower dividend yields, where divestitures appear to occur on the days before and shortly after the ex-dividend date. We interpret this as evidence of equity trading after the ex-dividend date, which could be due to RH investors selling after the declaration date.

The analyses presented in this section are consistent with RH investors not actively seeking to avoid dividend-paying stocks in their taxable accounts. While we cannot access these investors' tax-deferred accounts or other trading accounts, we cannot determine to what extent their total holdings are tax-efficient. Despite this data limitation, we conclude that it does not appear that avoiding taxable income is a first-order concern among RH investors.

[Insert Table 4 Here]

[12] For simplicity, we run all analyses with firm fixed effects. Our inferences remain the same when excluding firm fixed effects.

4.2 Tax Loss Harvesting Analysis

Next, we turn our attention to tax loss harvesting. We present descriptive statistics for this analysis in Table 5. Panel A presents our descriptive statistics. One thing to note is that there is an uptick in RH users in 2020. This increase occurs after January and ends before December. Thus, the percentage of observations that fall within the December-January trading window is somewhat lower than the unconditional probability. We also note that the distribution of returns is somewhat right skewed, where the average value of *NegativeReturn* is 0.475, implying that about 47.5% of observations are equities that generate a negative February through November return. However, the average return (*FebNovMonthlyRet*) is just under 7%. We graph the average holdings for the two-year ends in our sample in Figure 2. In Panel A, we plot December 2018 to January 2019; in Panel B, we plot December 2019 to January 2020. These two figures tell a striking story: a lack of tax-induced selling in December. While there is some volatility around year-end in 2020, for the most part, there does not appear to be any large reductions in aggregate holdings of recently poor-performing stocks.

[Insert Figure 2 Here]

To provide stronger statistical support for the visual evidence in Figure 2, we present the equation (2) results in Table 5, Panel B. In columns (1) and (2), the dependent variable is the total number of investors. In columns (3) and (4), we present the changes in daily investors. Furthermore, columns (1) and (3) exclude firm-fixed effects, whereas columns (2) and (4) include firm-fixed effects. Including firm fixed effects helps to account for the fact that some stocks are more likely to be owned by RH investors (like Apple). Recall that our strongest prediction for tax loss harvesting is a negative coefficient on the interaction of *December* and *NegativeReturn*. However, we fail to find a statistically significant result for this interaction in any of the four

specifications. We interpret this result as evidence that RH investors are not engaging in tax-loss harvesting, which is consistent with RH investors not acting in a tax-efficient manner.[13]

[Insert Table 5 Here]

In an additional analysis, we focus our attention on small-cap stocks. We do this because prior literature suggests that tax-loss harvesting is more likely to be present among these smaller firms (Sikes 2014). Thus, we examine this subset to mitigate concerns that the tax-loss harvesting result is not present in this group of small firms. To perform this analysis, we limit the sample to companies whose share price is less than $5 on average over the sample period. This results in a reduction in our N from slightly under 1.5 million to approximately 240 thousand observations. We follow the same dependent variables and fixed effects pattern as in the previous table. Once again, we fail to find evidence of tax loss selling in the ten trading days before year-end. Collectively, these analyses suggest that taxes are not driving the trading behavior of RH investors.

[Insert Table 6 Here]

4.2 Capital Gains Lock-In Analysis

Finally, we examine capital gains lock-in. We first examine the top herding events in our sample and graph holdings around the one-year mark from the herding event. The top two events, purchases of Facebook and Nike, with increases of 42,000 and 8,400 investors, respectively, are substantially larger than the third highest event (an increase of 991 investors) and are graphed separately in Figures 3a and 3b. We observe slight decreases in both companies after the one-year mark. However, Facebook already faces a downward trend in investors, making it difficult to discern whether the decrease in investors at the one-year mark is due to this time-trend or tax

[13] One concern about this analysis is that the increase in popularity of RH in 2020 after January may be masking our findings. In an untabulated analysis, we repeat this analysis excluding observations after January 2020. We continue to fail to find evidence of tax loss selling.

savviness. Additionally, when examining the two figures, we note that any later decrease pales in comparison to the initial herding event. Additionally, when examining the two figures, we note that any later decrease pales in comparison to the initial herding events. Figure 3c presents a similar graph for the next four largest herding events. We similarly fail to see strong evidence of investors selling their holdings after the one-year mark. Coupled with the results from Figures 3a and 3b, we find a lack of evidence of tax-induced selling at the end of the capital gains lock-in period.

[Insert Figure 3 Here]

To provide a more robust analysis, we estimate equation (3). Select descriptive statistics for this analysis are presented in Table 7, Panels A and B. Panel A (B) provides descriptives *just* for the day of (the trading days one year after) the herding event. For the 420 herding events in our full sample, the average increase in the number of investors holding a stock on the day of the herding event is 170. We find that the companies with herding events experience an increase in their investors, on average, based on the average *Investors* in Panel B compared to Panel A. Finally, because we only examine herding events for stocks with a capital gain (e.g., the price on the days one year after a herding event is higher than the price on the day of the herding event), the average stock price in Panel B is higher than in Panel A ($48.25 versus $36.62).

The equation (3) results are presented in Table 7, Panel C. In columns (1) and (2), the dependent variable is the number of investors, and in columns (3) and (4), the dependent variable is the changes in daily investors. Columns (1) and (3) exclude fixed effects, whereas columns (2) and (4) present results with firm fixed effects. If RH investors are tax savvy, our expectation is of a negative coefficient beginning on *YearLater_0*, which would be indicative of RH investors divesting their holdings once they qualify for long-term capital gains rates. However, our results

suggest that this isn't the case. Rather, we fail to find evidence of a decrease in holdings at the one-year mark, consistent with a lack of tax-induced selling.

[Insert Table 7 Here]

5. Conclusion

Since the inception of apps like Robinhood and others that allow trading from mobile devices, the equity trading markets (and the investors who comprise those markets) have dramatically shifted. A significant portion of prior literature and our knowledge surrounding whether retail investors act efficiently regarding taxes draws from data generated in the 1990s. Accordingly, we revisit the research question from Barber and Odean (2004) to ask a simple question: Are retail investors tax-savvy in current times? We specifically use data provided by Robinhood to determine whether the conclusion that individual investors understand and impound taxes into their investment decisions holds up among a new breed of investors in this current era of technology and investing. Using data on the number of traders holding a specific position over the span of approximately two years, we operationalize our research question by examining asset allocation decisions and tax loss harvesting. Specifically, we find that RH investors do not avoid dividend income in their taxable trading account and even appear to be drawn to high dividend yield equities before the ex-dividend date. Additionally, we see no evidence of tax loss harvesting in December or capital-gains lock-in trading one year after herding events. We conclude that RH investors do not appear to be tax savvy.

The financial press has declared that "Pandemic, zero-commission trading 'created a whole generation of investors'" (Miao, 2023). Since the COVID-19 pandemic, household exposure to the equity market increased in the U.S. (Federal Board of Reserve 2023). However, many commentators are concerned about whether inexperienced investors' trading patterns are

truly beneficial or more akin to gambling (Farivar 2021). We fill the literature void to determine whether RH investors trade in response to tax considerations. This question is important to the asset pricing literature and the public finance debate on optimal levels of taxation of equity investments. As policymakers aim to create a tax system that balances investment and risk-taking with the need to raise capital through tax revenues, our research speaks to whether taxes are distortionary to a major category of retail investors (RH has over 13 million users).

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Appendix A

Variable	Definition
AllDividendsAmt	is sum of regular and special dividends per share paid by firm *i* during the fiscal year of day *d*.
December	equals 1 if an observation is within the last 10 trading days of December, and 0 otherwise.
DivPayerThisYr	equals 1 if firm *i* paid a dividend in the fiscal year of day *d*, and 0 otherwise.
Div_Yield_All	is the absolute value of the dividend divided by the share price on the last cumulative dividend day.
Feb_Nov_MonthlyRet	is the cumulative monthly return from February through November for the fiscal year of day *d.*
Investors	is the number of Robinhood investors invested in firm *i* on day *d.*
Investors_chg	is the change in Robinhood investors from day *d-1* to day *d* in firm *i.*
January	equals 1 if an observation is within the first 10 trading days of January, and 0 otherwise.
LogInvestors	is the natural log of the number of Robinhood investors invested in firm *i* on day *d.*
NegativeReturn	equals 1 if *Fed_Nov_MonthlyRet* is less than 0, and 0 otherwise.
Price	is the closing price.
RegDivsThisYr	is sum of regular dividends per share paid by firm *i* during the fiscal year of day *d*.
T_pre_X	is an indicator equal to 1 for the X number of days before the ex-dividend date.
T_X	is an indicator equal to 1 for the X number of days after the ex-dividend date.
YearLater_pre_X	is an indicator equal to 1 for the X number of days before the day that is one calendar year and a day after a herding event.
YearLater_X	is an indicator equal to 1 for the X number of days after the day that is one calendar year and a day after a herding event.

Figure 1: Holdings Around Ex-Dividend Date

Panel A: Total Number of Robinhood Investors

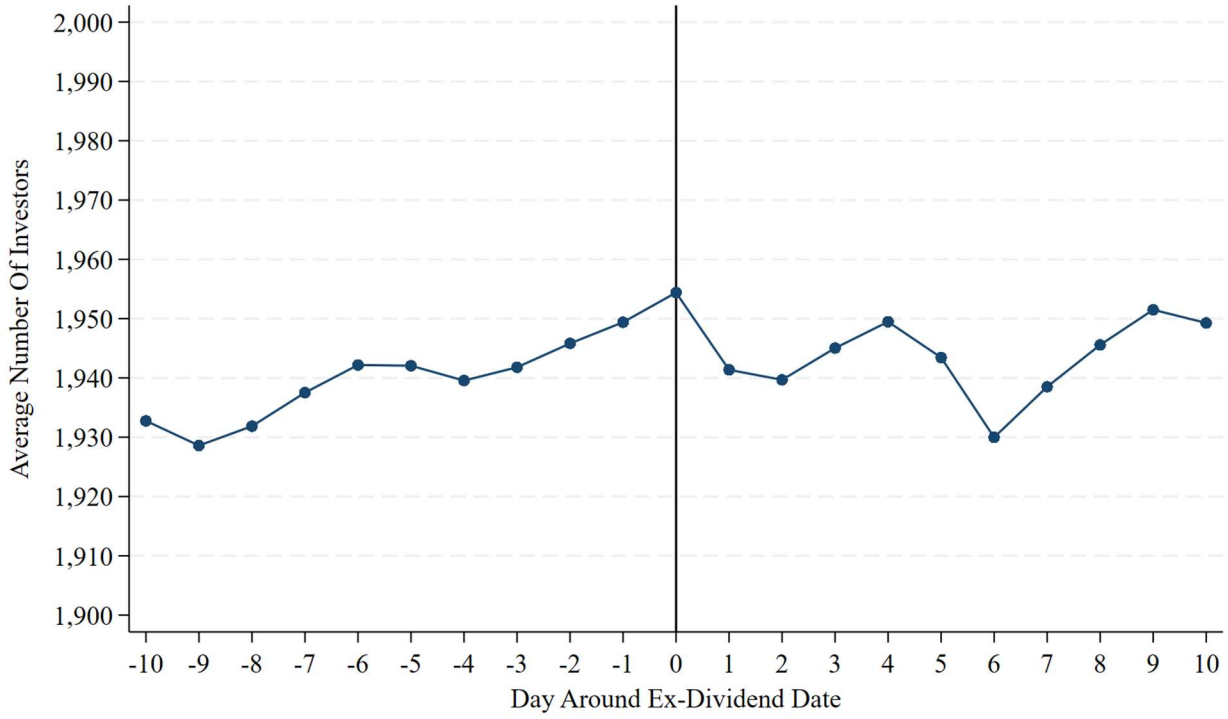

Figure 1: Holdings Around Ex-Dividend Date (continued)

Panel B: Changes in the number of Robinhood investors

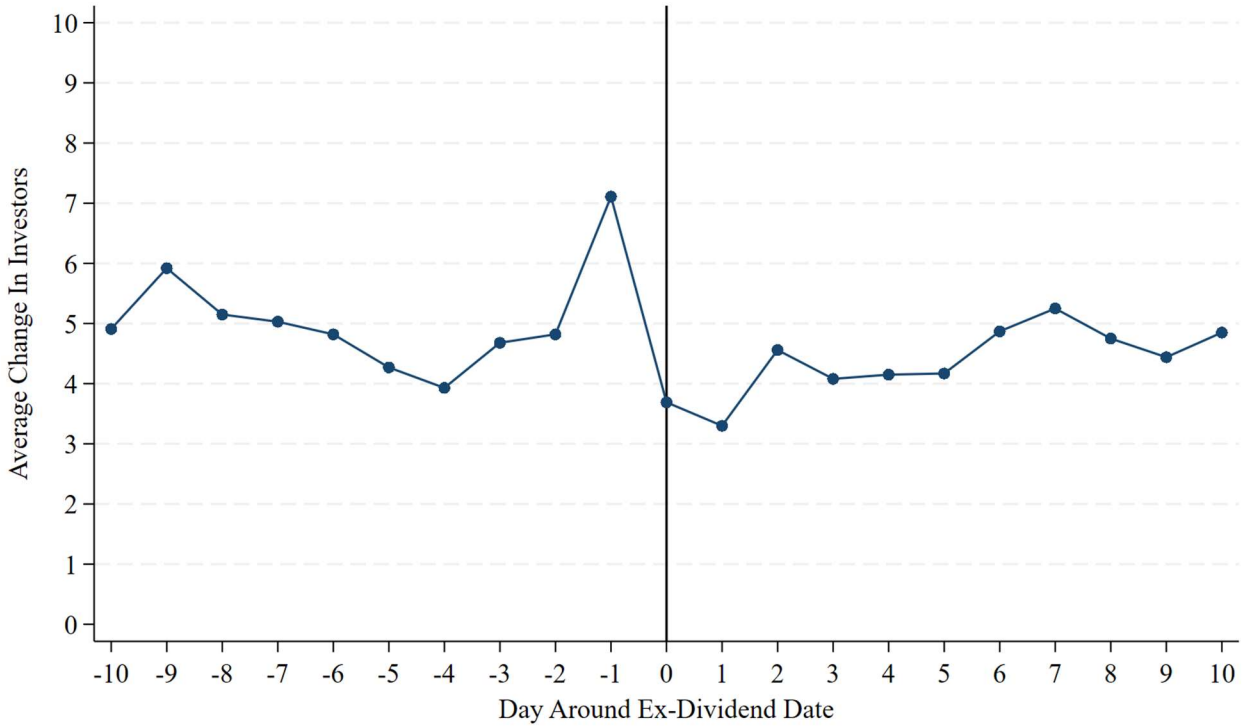

Figure 1, Panels A and B depict the average investors holding Robinhood stocks around the ex-dividend date. Panel A graphs the average number of investors, and Panel B graphs day-to-day changes in the average number of investors.

Figure 2: Average Robinhood Holdings Around the "Turn-of-the-Year"

Panel A: 2018-2019

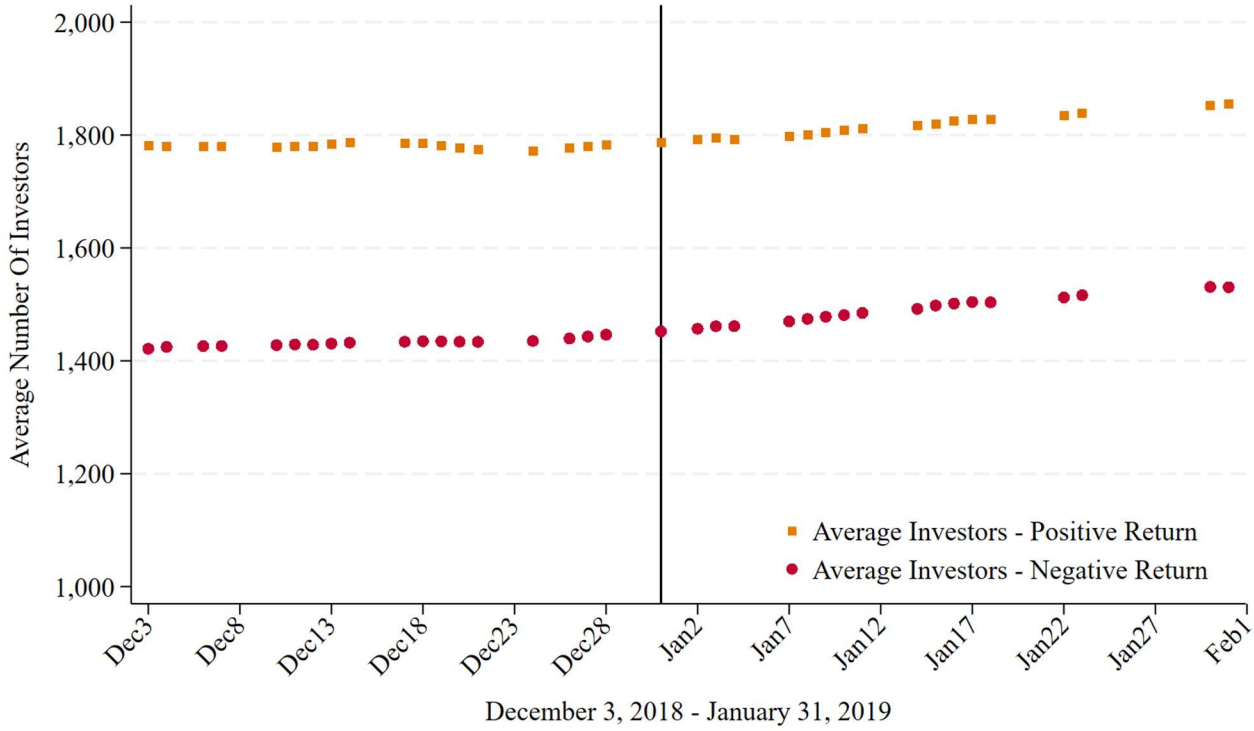

Figure 2: Average Robinhood Holdings Around the "Turn-of-the-Year" (continued)

Panel B: 2019-2020

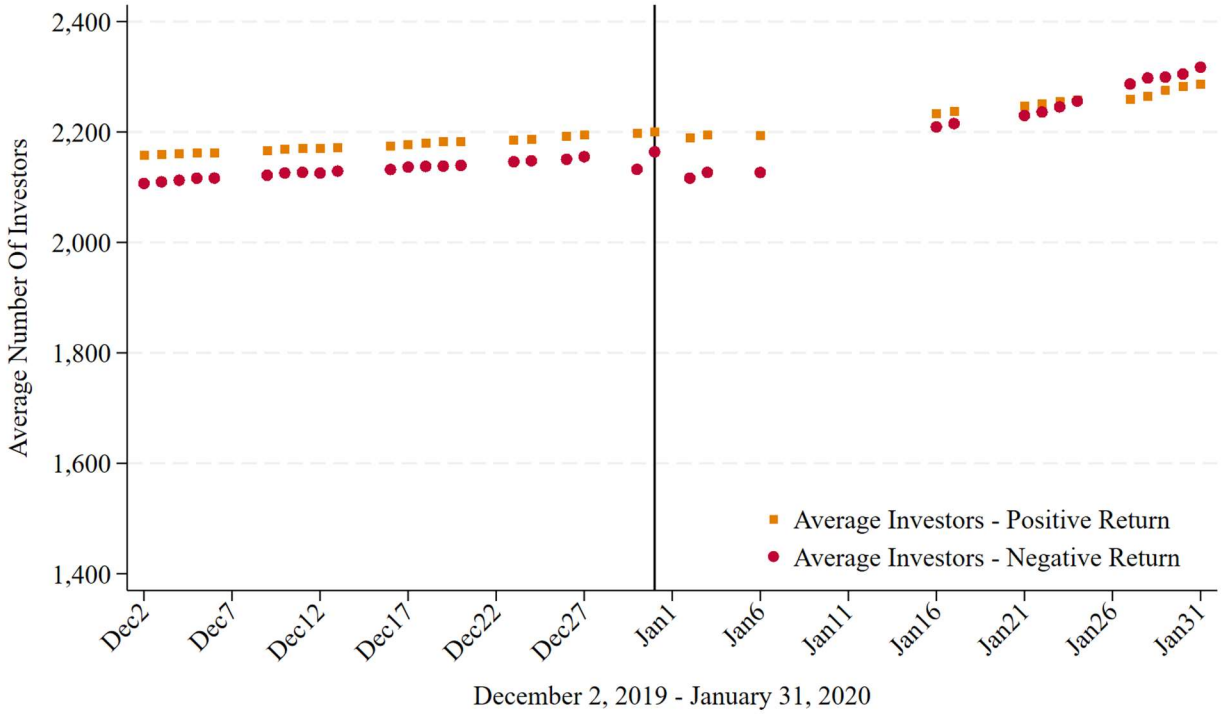

Figure 2, Panels A and B depict the average number of investors holding Robinhood stocks graphed over December of the current year and January of the following year, split by stocks with a positive or negative monthly return during the course of the current year from February through November. Panel A graphs December 2018 through January 2019, and Panel B graphs December 2019 through January 2020.

Figure 3: Number of Robinhood Investors After Herding Events

Panel A: Facebook

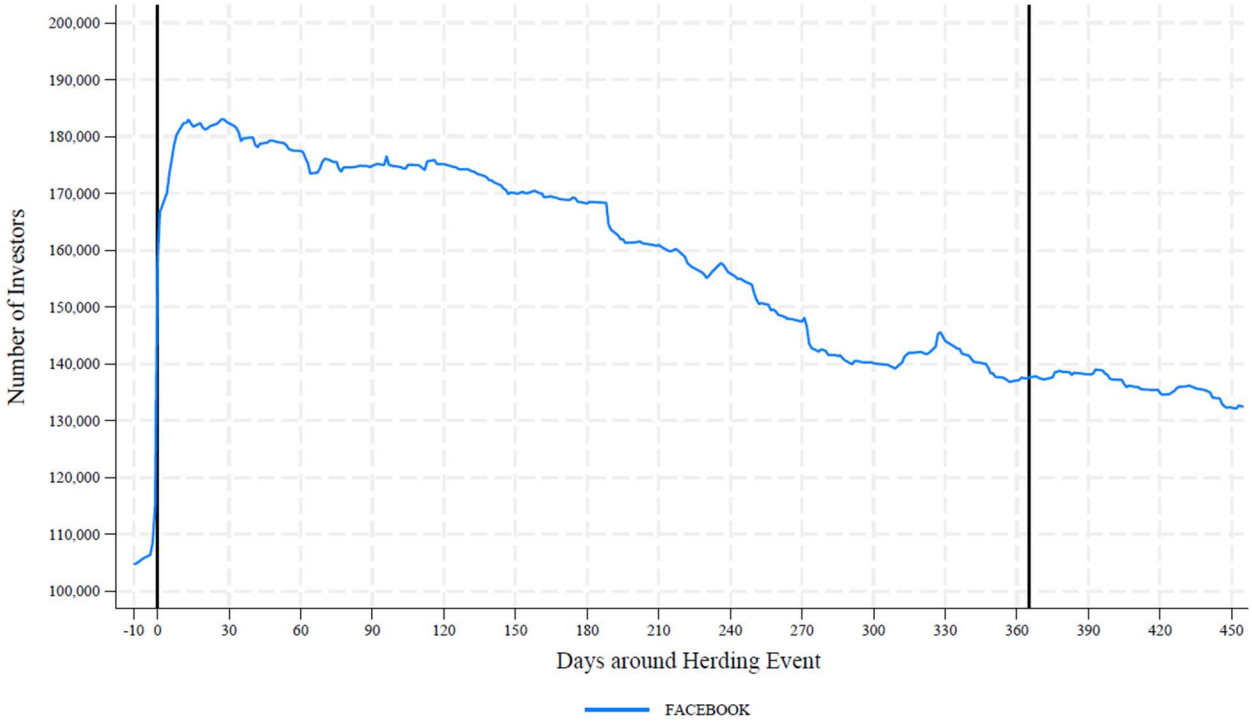

Figure 3: Number of Robinhood Holdings After Herding Events (continued)

Panel B: Nike

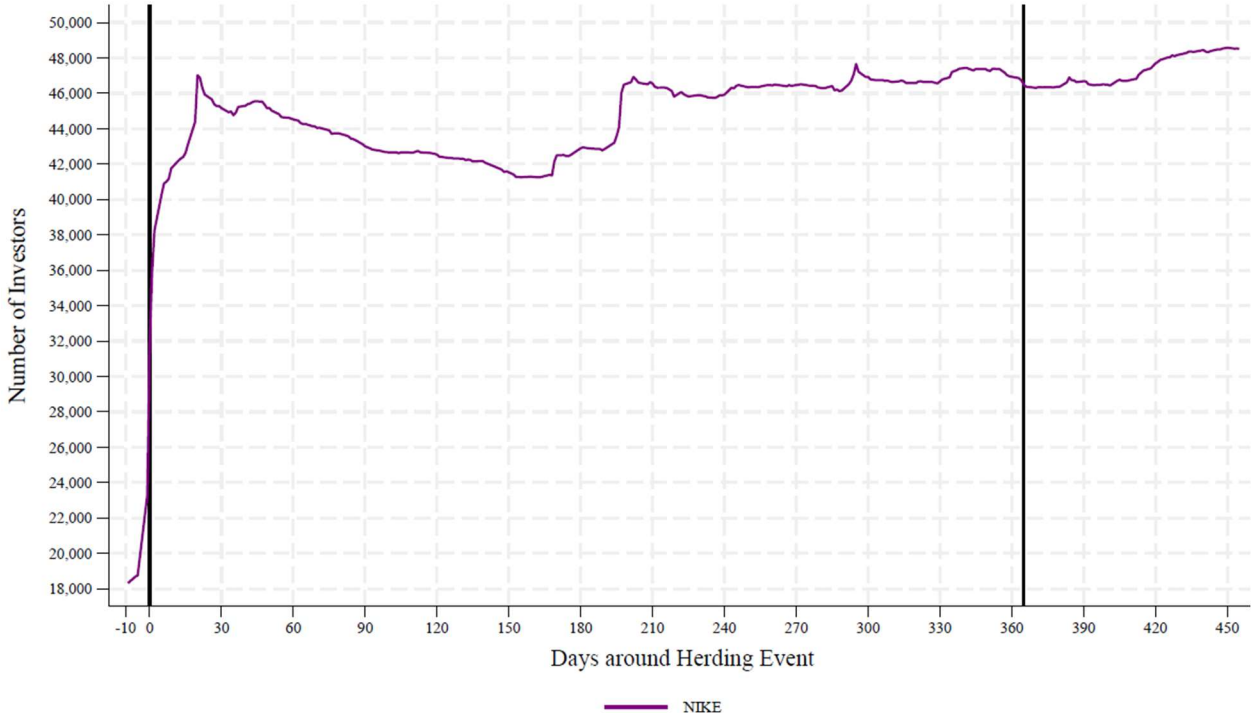

Figure 3: Number of Robinhood Holdings After Herding Events (continued)

Panel C: Lumentum Holdings, MiTek Systems, Skechers, and Arrowhead Pharmaceuticals

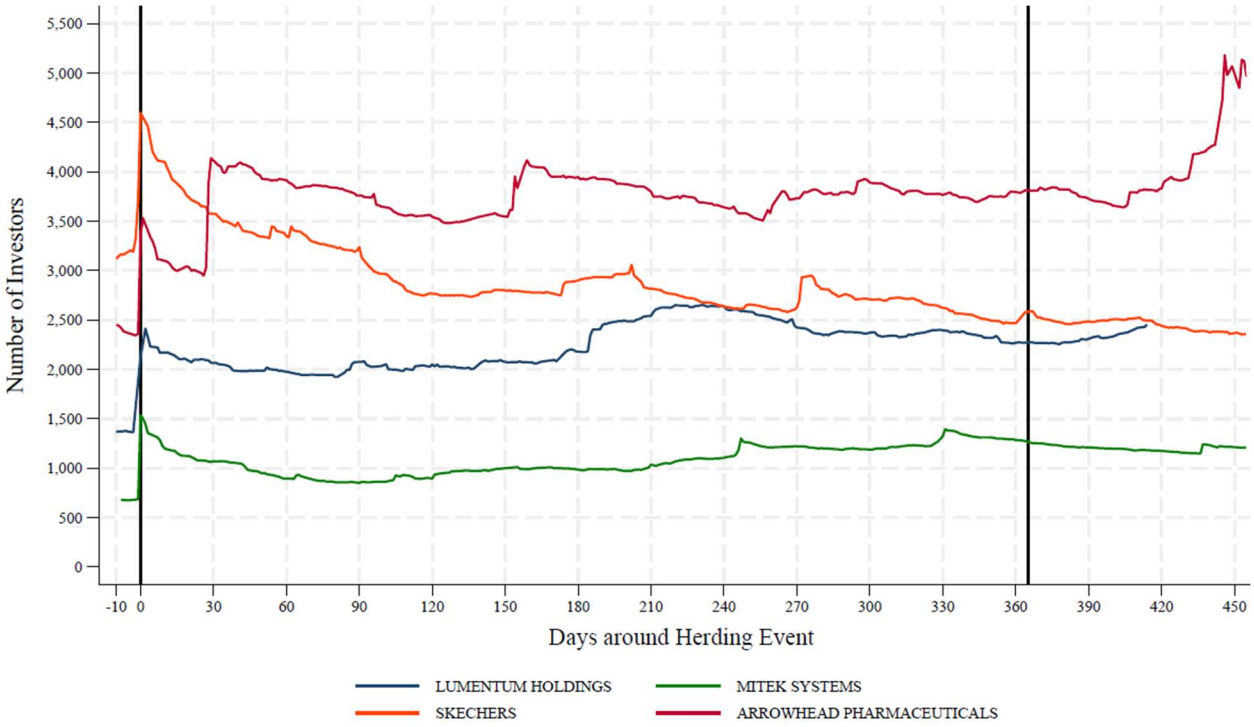

Figure 3, Panels A – C depict the number of investors holding Facebook (Panel A), Nike (Panel B), and Lumentum Holdings, MiTek Systems, Skechers, and Arrowhead Pharmaceuticals (Panel C) for the (-10,450) day period around a herding event. The number of investors is graphed in event time. The first vertical line marks the day of the herding event (e.g., day 0) and the second vertical line marks the day that is one year after the herding event (e.g., day 365).

Table 1. Sample Selection

	# of Observations
Ticker-day observations in CRSP and Compustat Quarterly from June 1, 2018 and August 13, 2020	2,555,574
Less:	
Firms that change sharecodes	51,446
Observations with sharecodes other than 10 and 11	629,135
Firms with multiple share classes	23,365
Firms without one observation in Robinhood per quarter	330,941
Observations missing data needed to construct variables	64,454
Total observations in final sample	1,456,233
Total unique firms in final sample	2,748

Table 2. Descriptive Statistics for Ex-Dividend Day Analysis

Panel A: Firms Paying a Regular or Special Dividend

	N	Mean	Median	P25	P75
Investors	679,317	2,107.085	204.000	57.000	818.000
LogInvestors	679,317	5.512	5.323	4.060	6.708
Investors_chg	674,313	5.057	0.000	-1.000	2.000
AllDividendsAmt	10,283	.307	0.220	.12	.39
Div_Yield_All	212,659	.007	0.006	.003	.008

Panel B: Firms Paying No Dividend

	N	Mean	Median	P25	P75
Investors	776,916	3,386.263	433.000	150.000	1,348.000
LogInvestors	776,916	6.168	6.073	5.017	7.207
Investors_chg	771,166	4.665	0.000	-3.000	2.000

Panel C: CRSP/Compustat Universe

	Robinhood		CRSP/Compustat Universe		
	N	Mean	*N*	Mean	Difference
RegDivsThisYr	1,456,233	0.525	1,851,628	0.446	0.079***
DivPayerThisYr	1,456,233	0.461	1,851,628	0.408	0.052***

This table reports descriptive statistics for the dividend paying stock analysis. Panel A presents descriptive statistics for firm-year observations in which the firm pays a regular or a special dividend during the year, and Panel B presents descriptive statistics for firm-year observations in which the firm does not pay a regular or special dividend during the year. Panel C compares Robinhood users' holdings to the entire universe of Compustat and CRSP. All continuous variables are winsorized at the 1st and 99th percentile. Variable definitions can be found in Appendix A.

Table 3: Ex-Dividend Day Analyses

Panel A: Average Investors Around Ex-Dividend Date (Regular Dividends)

	N	Mean	Median	P25	P75
T_pre_10	9,922	1,943	196	54	786
T_pre_9	10,026	1,937	195	54	784
T_pre_8	10,052	1,940	197	54	787
T_pre_7	10,061	1,945	199	55	788
T_pre_6	10,067	1,950	201	55	791
T_pre_5	10,089	1,951	201	55	794
T_pre_4	10,146	1,948	201	55	795
T_pre_3	10,156	1,950	201	55	795
T_pre_2	10,169	1,954	203	56	801
T_pre_1	10,186	1,958	205	58	806
T_0	10,202	1,962	204	57	808
T_1	10,132	1,951	203	57	801
T_2	10,117	1,949	203	57	803
T_3	10,105	1,955	203	57	804
T_4	10,092	1,959	202	57	805
T_5	10,055	1,953	201	57	802
T_6	10,010	1,939	203	56	804
T_7	9,995	1,948	203	56	808
T_8	9,988	1,955	203	56	814
T_9	9,968	1,961	203	56	810
T_10	9,952	1,960	204	56	815

Table 3: Ex-Dividend Day Analyses (continued)

Panel B: Ex-Dividend Day Analysis

VARIABLES	(1) *Investors*	(2) *Investors*	(3) *Investors_chg*	(4) *Investors_chg*
T_pre_10	-415.95**	-217.53***	0.04	-0.27
	(-2.40)	(-6.32)	(0.07)	(-0.71)
T_pre_9	-420.11**	-216.78***	1.04*	0.74*
	(-2.44)	(-6.27)	(1.90)	(1.95)
T_pre_8	-416.85**	-211.07***	0.28	0.00
	(-2.42)	(-6.11)	(0.58)	(0.01)
T_pre_7	-411.19**	-206.08***	0.16	-0.11
	(-2.38)	(-5.97)	(0.34)	(-0.32)
T_pre_6	-406.53**	-201.73***	-0.05	-0.34
	(-2.36)	(-5.82)	(-0.10)	(-0.93)
T_pre_5	-406.66**	-199.42***	-0.60	-0.88**
	(-2.36)	(-5.72)	(-1.23)	(-2.43)
T_pre_4	-409.17**	-200.55***	-0.94**	-1.21***
	(-2.38)	(-5.68)	(-2.13)	(-3.52)
T_pre_3	-406.91**	-196.91***	-0.19	-0.46
	(-2.37)	(-5.58)	(-0.44)	(-1.31)
T_pre_2	-402.90**	-195.31***	-0.05	-0.34
	(-2.34)	(-5.48)	(-0.10)	(-0.98)
T_pre_1	-399.33**	-189.38***	2.24***	1.96***
	(-2.33)	(-5.32)	(4.48)	(5.20)
T_0	-394.32**	-191.02***	-1.18**	-1.44***
	(-2.29)	(-5.30)	(-2.19)	(-3.78)
T_1	-407.35**	-202.79***	-1.57***	-1.85***
	(-2.38)	(-5.75)	(-3.49)	(-5.37)
T_2	-409.03**	-203.86***	-0.31	-0.60*
	(-2.39)	(-5.80)	(-0.68)	(-1.91)
T_3	-403.68**	-200.09***	-0.79*	-1.06***
	(-2.35)	(-5.71)	(-1.85)	(-3.33)
T_4	-399.25**	-197.22***	-0.72	-1.03***
	(-2.32)	(-5.65)	(-1.59)	(-3.16)
T_5	-405.28**	-198.88***	-0.70	-1.00***
	(-2.37)	(-5.74)	(-1.64)	(-3.62)
T_6	-418.75**	-204.10***	-0.01	-0.30
	(-2.48)	(-5.93)	(-0.02)	(-1.01)
T_7	-410.21**	-198.22***	0.37	0.08
	(-2.43)	(-5.80)	(0.78)	(0.25)
T_8	-403.14**	-192.67***	-0.12	-0.41
	(-2.38)	(-5.68)	(-0.26)	(-1.31)
T_9	-397.21**	-188.28***	-0.44	-0.74**
	(-2.34)	(-5.63)	(-0.96)	(-2.06)
T_10	-399.44**	-189.58***	-0.02	-0.28

	(-2.35)	(-5.75)	(-0.05)	(-0.88)
Constant	2,348.71***	2,318.49***	4.87***	4.91***
	(16.52)	(460.55)	(17.12)	(175.85)
Observations	1,456,233	1,456,233	1,445,479	1,445,479
Adjusted R-squared	0.000	0.827	0.000	0.137
Fixed Effects	None	Firm	None	Firm
SE Cluster	Firm	Firm	Firm	Firm

Panel A reports descriptive statistics for the number of investors holding Robinhood stock during the ten days before and the ten days after the ex-dividend date for regular dividends Panel B presents the results from estimating Eq. (1). The dependent variable in columns (1) and (2), *Investors*, is the average number of investors holding a Robinhood stock. The dependent variable in columns (3) and (4), *Investors_chg*, is the average change in the number of investors holding a Robinhood stock from the prior day to the current day. Variable definitions can be found in Appendix A. Standard errors are clustered at the firm-level. All continuous variables are winsorized at the 1st and 99th percentile. We report t-statistics in parenthesis. *, **, *** signify statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively, using two-tailed tests.

Table 4. Ex-Dividend Day Analysis Split by Dividend Yield

	Low Dividend Yield Quintile		High Dividend Yield Quintile	
	(1)	(2)	(3)	(4)
VARIABLES	*Investors*	*Investors_chg*	*Investors*	*Investors_chg*
T_pre_10	-63.91	0.40	-164.03	2.61***
	(-0.95)	(0.45)	(-1.52)	(2.73)
T_pre_9	-65.22	0.72	-158.66	3.90***
	(-0.97)	(0.78)	(-1.44)	(3.81)
T_pre_8	-62.19	-0.52	-143.79	3.80***
	(-0.93)	(-0.71)	(-1.30)	(3.93)
T_pre_7	-58.85	-0.91	-133.63	2.93***
	(-0.87)	(-1.03)	(-1.21)	(3.11)
T_pre_6	-55.23	-0.40	-127.76	3.69***
	(-0.82)	(-0.49)	(-1.14)	(3.74)
T_pre_5	-52.49	0.17	-120.28	2.58***
	(-0.78)	(0.17)	(-1.07)	(2.72)
T_pre_4	-51.68	-2.64***	-117.21	1.77**
	(-0.77)	(-3.08)	(-1.04)	(2.33)
T_pre_3	-48.75	-1.46**	-109.02	2.92***
	(-0.72)	(-2.23)	(-0.96)	(2.92)
T_pre_2	-48.28	-2.09***	-98.36	3.65***
	(-0.72)	(-3.18)	(-0.87)	(3.68)
T_pre_1	-46.71	-0.57	-83.39	9.31***
	(-0.70)	(-0.71)	(-0.74)	(8.64)
T_0	-67.40	-1.07	-101.63	1.29
	(-0.97)	(-1.18)	(-0.88)	(1.21)
T_1	-77.00	-0.81	-101.26	-1.14
	(-1.13)	(-0.91)	(-0.90)	(-1.59)
T_2	-70.38	-0.78	-112.80	0.89
	(-1.05)	(-1.48)	(-0.99)	(0.97)
T_3	-67.93	-2.02***	-105.62	0.26
	(-1.02)	(-2.99)	(-0.93)	(0.39)
T_4	-65.90	-1.43**	-98.25	1.04
	(-0.99)	(-2.18)	(-0.87)	(1.36)
T_5	-75.32	-0.91	-97.36	1.05
	(-1.14)	(-1.31)	(-0.87)	(1.36)
T_6	-77.84	-0.72	-99.37	2.40***
	(-1.20)	(-1.10)	(-0.86)	(2.94)
T_7	-74.96	-0.27	-89.47	1.78**
	(-1.15)	(-0.44)	(-0.77)	(2.28)
T_8	-72.96	-0.83	-78.23	2.42***
	(-1.12)	(-1.47)	(-0.67)	(2.86)
T_9	-71.63	-1.93***	-73.46	1.62
	(-1.10)	(-2.78)	(-0.63)	(1.50)
T_10	-68.09	-0.63	-94.01	1.39

	(-1.04)	(-0.73)	(-0.83)	(1.59)
Constant	2,340.18***	4.87***	2,358.64***	4.93***
	(1,062.66)	(338.47)	(637.36)	(258.45)
Observations	1,286,095	1,276,357	1,285,868	1,276,200
Adjusted R-squared	0.825	0.134	0.820	0.136
Fixed Effects	Firm	Firm	Firm	Firm
SE Cluster	Firm	Firm	Firm	Firm

This table reports the results from estimating Eq. (1) for the lowest and highest quintiles of dividend yield. Columns (1) and (2) present results for lowest quintile, and columns (3) and (4) present results for the highest quintile. In columns (1) and (3), the dependent variable is *Investors,* and in columns (2) and (4) the dependent variable is *Investors_chg.* Variable definitions can be found in Appendix A. For brevity, we report all results with firm fixed effects. Our inferences remain unchanged when we do not use fixed effects. Standard errors are clustered at the firm-level. All continuous variables are winsorized at the 1st and 99th percentile. We report t-statistics in parenthesis. *, **, *** signify statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively, using two-tailed tests.

Table 5. Tax Loss Harvesting Analysis

Panel A: Descriptive Statistics

	N	Mean	Median	P25	P75
December	1,456,233	0.037	0.000	0.000	0.000
January	1,456,233	0.024	0.000	0.000	0.000
Investors	1,456,233	2,289	312	95	1,110
LogInvestors	1,456,233	5.860	5.746	4.564	7.013
Investors_chg	1,445,479	4.848	0.000	-2.000	2.000
NegativeReturn	1,456,233	0.475	0.000	0.000	1.000
Feb Nov MonthyRet	1,456,233	0.069	0.022	-0.185	0.234

Panel B: Regression Analysis

	(1)	(2)	(3)	(4)
VARIABLES	*Investors*	*Investors*	*Investors_chg*	*Investors_chg*
December	-504.94***	-388.48***	-2.47***	-2.46***
	(-9.17)	(-12.47)	(-8.30)	(-8.62)
NegativeReturn	-458.62**	-122.59	-0.02	1.07***
	(-2.47)	(-1.38)	(-0.05)	(2.74)
*December*NegativeReturn*	162.79	-81.11	-0.29	-0.34
	(1.50)	(-1.49)	(-0.63)	(-0.83)
January	-608.37***	-529.13***	-1.04***	-1.09***
	(-7.06)	(-13.07)	(-2.77)	(-3.10)
*January*NegativeReturn*	131.47	-62.05	0.02	-0.04
	(0.81)	(-0.95)	(0.04)	(-0.09)
Constant	2,535.69***	2,376.82***	4.98***	4.47***
	(13.30)	(56.38)	(12.82)	(24.35)
Observations	1,456,233	1,456,233	1,445,479	1,445,479
Adjusted R-squared	0.001	0.828	0.000	0.137
Fixed Effects	None	Firm	None	Firm
SE Cluster	Firm	Firm	Firm	Firm

Panel A of this table reports descriptive statistics for the turn-of-the-year analysis. Panel B of this table presents the results from estimating Eq. (2). The dependent variable in columns (1) and (2), *Investors*, is the average number of investors holding a Robinhood stock. The dependent variable in columns (3) and (4), *Investors_chg*, is the average change in the number of investors holding a Robinhood stock from the prior day to the current day. Variable definitions can be found in Appendix A. Standard errors are clustered at the firm-level. All continuous variables are winsorized at the 1st and 99th percentile. We report t-statistics in parenthesis. *, **, *** signify statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively, using two-tailed tests.

Table 6: Tax Loss Harvesting Among Small Cap Stocks

VARIABLES	(1) *Investors*	(2) *Investors*	(3) *Investors_chg*	(4) *Investors_chg*
December	-1,261.83***	-868.70***	-1.88	-1.31
	(-4.81)	(-5.55)	(-1.64)	(-1.24)
NegativeReturn	-1,031.45**	-1,474.16***	-1.73	-2.85***
	(-2.26)	(-4.46)	(-1.61)	(-3.34)
*December*NegativeReturn*	1,034.97***	537.21***	1.27	0.60
	(3.14)	(2.85)	(0.82)	(0.43)
January	-1,474.75***	-1,030.70***	-1.58	-0.49
	(-3.87)	(-5.97)	(-1.16)	(-0.42)
*January*NegativeReturn*	1,006.84**	455.19**	1.64	0.31
	(2.03)	(2.13)	(0.93)	(0.21)
Constant	3,400.15***	3,700.03***	6.57***	7.32***
	(7.34)	(16.39)	(6.13)	(12.75)
Observations	241,718	241,718	239,923	239,923
Adjusted R-squared	0.004	0.686	0.000	0.091
Fixed Effects	None	Firm	None	Firm
SE Cluster	Firm	Firm	Firm	Firm

This table presents the results from estimating Eq. (2) among a sample of firms whose stock price is less than $5 on average over the sample period. The dependent variable in columns (1) and (2), *Investors*, is the average number of investors holding a Robinhood stock. The dependent variable in columns (3) and (4), *Investors_chg*, is the average change in the number of investors holding a Robinhood stock from the prior day to the current day. Variable definitions can be found in Appendix A. Standard errors are clustered at the firm-level. All continuous variables are winsorized at the 1st and 99th percentile. We report t-statistics in parenthesis. *, **, *** signify statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively, using two-tailed tests.

Table 7: Capital Gains Lock-In Analysis

Panel A: Descriptive Statistics for Day of Herding Event

	N	Mean	Median	p25	p75
Investors	420	1,190	474	248	1,046
Investors_chg	420	170	154	65	300
Price	420	36.62	18.39	5.76	50.74

Panel B: Descriptive Statistics for Trading Days One Year After Herding Events

	N	Mean	Median	p25	p75
Investors	7,035	2,367	626	259	1,601
Investors_chg	6,994	4	0	(4)	3
Price	7,035	48.25	27.12	8.67	65.51

Panel C: Regression Analysis

	(1)	(3)	(7)	(9)
VARIABLES	*Investors*	*Investors*	*Investors_chg*	*Investors_chg*
YearLater_pre_10	3.13	542.54***	-2.52	-0.64
	(0.01)	(3.12)	(-1.08)	(-0.27)
YearLater_pre_9	72.17	583.12***	4.06	5.85**
	(0.19)	(3.33)	(1.32)	(1.97)
YearLater_pre_8	-30.94	550.02***	-1.61	0.39
	(-0.08)	(3.21)	(-0.60)	(0.15)
YearLater_pre_7	-14.65	542.84***	-1.31	0.53
	(-0.04)	(2.89)	(-0.53)	(0.21)
YearLater_pre_6	-13.41	526.75***	-1.00	0.84
	(-0.04)	(2.88)	(-0.40)	(0.34)
YearLater_pre_5	-52.50	497.06***	3.57	5.42**
	(-0.14)	(2.87)	(1.32)	(2.16)
YearLater_pre_4	-71.04	494.64***	-1.93	-0.05
	(-0.19)	(2.90)	(-0.81)	(-0.02)
YearLater_pre_3	-32.59	503.65***	1.59	3.41
	(-0.09)	(2.94)	(0.62)	(1.38)
YearLater_pre_2	48.84	544.19***	-0.19	1.54
	(0.13)	(2.99)	(-0.07)	(0.61)
YearLater_pre_1	105.66	602.16***	-3.74	-1.94
	(0.27)	(3.12)	(-1.57)	(-0.81)
YearLater_0	169.42	689.32***	-3.26	-1.37
	(0.43)	(3.44)	(-1.44)	(-0.63)
YearLater_1	172.62	683.04***	-1.49	0.33
	(0.44)	(3.42)	(-0.64)	(0.14)
YearLater_2	-17.01	584.47***	-1.85	0.07
	(-0.05)	(3.47)	(-0.79)	(0.03)
YearLater_3	199.96	730.68***	-1.57	0.32

	(0.50)	(3.59)	(-0.67)	(0.14)
YearLater_4	171.60	700.32***	-4.12**	-2.23
	(0.43)	(3.54)	(-2.19)	(-1.23)
YearLater_5	115.96	661.15***	2.21	4.07
	(0.29)	(3.39)	(0.79)	(1.54)
YearLater_6	175.53	709.75***	1.96	3.86
	(0.43)	(3.56)	(0.71)	(1.46)
YearLater_7	153.72	705.13***	-3.23	-1.36
	(0.38)	(3.53)	(-1.54)	(-0.71)
YearLater_8	172.80	721.93***	-4.08*	-2.31
	(0.43)	(3.69)	(-1.93)	(-1.25)
YearLater_9	82.61	653.20***	-3.71*	-1.87
	(0.20)	(3.34)	(-1.89)	(-1.00)
YearLater_10	225.71	755.34***	-1.31	0.48
	(0.54)	(3.67)	(-0.57)	(0.22)
Constant	2,288.86***	2,286.25***	4.85***	4.84***
	(16.52)	(2,724.15)	(17.11)	(1,065.09)
Observations	1,456,233	1,456,233	1,445,479	1,445,479
Adjusted R-squared	-0.000	0.827	0.000	0.137
Fixed Effects	None	Firm	None	Firm
SE Cluster	Firm	Firm	Firm	Firm

Panels A and B of this table report descriptive statistics for the capital gains lock-in analysis. Panel A (B) presents descriptives for the day of (the trading days one year after) the herding events for firms that experience a herding event. Herding events are defined following Barber et al. (2022) and are further restricted to stocks with a capital gain one year after the event. Panel C of this table presents the results from estimating Eq. (3). The dependent variable in columns (1) and (2), *Investors*, is the average number of investors holding a Robinhood stock. The dependent variable in columns (3) and (4), *Investors_chg*, is the average change in the number of investors holding a Robinhood stock from the prior day to the current day. Variable definitions can be found in Appendix A. Standard errors are clustered at the firm-level. All continuous variables are winsorized at the 1st and 99th percentile. We report t-statistics in parenthesis. *, **, *** signify statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively, using two-tailed tests.