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THE WISDOM OF THE ROBINHOOD CROWD

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ABSTRACT

Robinhood (RH) investors collectively increased their holdings in the March 2020 COVID bear market, indicating an absence of panic and margin calls. Their steadfastness was rewarded in the subsequent bull market. Despite unusual interest in some “experience” stocks, their aggregated consensus portfolio (likely mimicking the household-equal-weighted portfolio) primarily tilted towards stocks with high past share volume and dollar-trading volume. These were mostly big stocks. Both their timing and their consensus portfolio performed well from mid-2018 to mid-2020.

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The online retail brokerage company Robinhood (RH) was founded in 2013 based on a business plan to make it easier and cheaper for small investors to participate in the stock and option markets. RH never charged brokerage fees, which allowed their clients to buy and sell single (and even fractional) shares of stocks. RH's also appealed to customers with many other small technological innovations, such as a friendly mobile-first user interface. RH itself earns its own revenues through margin fees, cash balance interest, and payment-for-order flow.

As of mid-2020, RH had attracted a clientele of over 13 million investors—widely believed to be mostly small, young, computer-savvy but novice investors. The WSJ reported on Sep 12, 2020 that "According to Robinhood...first time investors accounted for 1.5 million of its 3 million funded accounts opened in the first four months of 2020." The website Brokerage-Review.com estimated that the average account size at RH was only $2,000. By August of 2020, RH had raised another $200 million of fresh capital, boosting its valuation to $11.2 billion. It is widely considered a disruptive force in US investing.

From mid-2018 to mid-2020, RH also offered an API that made it possible to obtain the number of (anonymous) RH investors (N_i) who held a particular stock i at that particular moment. In turn, the website Robintrack.net wrote some scripts to continuously pull down these holdings (at a speed of about 20 stocks per second, cycling through all stocks about once an hour) and then reposted the data online with RH's blessing. My paper investigates some aspects of this history.

1. Stock-Specific Changes in Holdings: Grinblatt and Keloharju (2001) and Barber and Odean (2008) had shown that retail investors in the 1990s had bought stocks that had recently gone up or down dramatically. They suggested this could be due to stocks catching the attention of investors (Barber and Odean (2008)) or deliberate sensationseeking (Grinblatt and Keloharju (2001)).[1] My paper shows that, even two decades later, these even smaller RH investors also purchased large gainers and losers.

2. Aggregate Changes in Holdings: Unfortunately, earlier studies did not include precipitous market declines, such as the market crash of 1987, the dot-com burst of 2000, or the financial crisis of 2008. In contrast, the 2018-2020 sample includes the COVID episode. This makes it possible to investigate retail behavior during a sharp market-wide downturn and quick subsequent recovery.

My paper shows that aggregate RH holdings also increased during this episode. RH investors did not panic or experience margin calls. Their first "purchasing" spike (i.e., an increase in the sum total number of holding investors in all stocks) occurred as early as the next day, presumably reflecting their existing purchasing power in their accounts. A second spike occurred about four days after a large market movement. This is roughly the time required to complete a cash bank transfer.

This evidence suggests that RH investors may have actively added cash to fund purchases of more stocks. Thus, during the March 2020 stock market decline, RH investors collectively acted as a (small) market-stabilizing force. (Because RH investors also buy after stock market increases, they may not be a stabilizing force in other situations. Indeed, they also added funds aggressively after large upswings.)

A simple thought experiment in which RH holdings represent market and non-holdings cash investments suggests that RH investors were lucky in their timing. They earned a lower mean rate of return but enjoyed a higher Sharpe ratio than the stock market.

[1] See also Ben-Rephael, Da, and Israelsen (2017); DellaVigna and Pollet (2009); Fang and Peress (2009); Fang and Peress (2009); Hirshleifer, Lim, and Teoh (2009); Peng and Xiong (2006); Da, Engelberg, and Gao (2011); and DellaVigna and Pollet (2009). Barber and Odean (2013) survey the behavioral literature on individual investors. Barber, Huang, et al. (2020) investigate stock-specific RH holding changes in more detail.

3. Level Holdings: Besides investigating somewhat different types of investors in different eras, most of the retail investor literature has focused on the timing of their trades. In contrast, my paper focuses on portfolio-level holdings rather than portfolio changes.

My paper shows that there is plenty of opportunity to poke fun at RH investors. For example, they overweighted stocks that seemed to appeal to their interests: Ford (but not GM), Facebook in 2018 (but not in 2020), and airline stocks in 2020 (but not in 2018). AMD, Snapchat, and Cannabis stocks were particularly popular. At the end of January 2019, Aurora Cannabis (ACB) was briefly the most widely held stock, with 244,532 investors! (AAPL was second with "only" 237,521 investors.) RH-type investors may very well have played a role in the active trading of, and the steady-state demand for, cannabis and many other (otherwise) obscure stocks.

Nevertheless, this narrative is a misleading. The "actual Robinhood" (ARH) portfolio was not nearly as crazy as these anecdotal tales would have it. Cannabis and other "experience holdings" were just minor sideshows. Most investment weight was not in these stocks.

This becomes obvious when we investigate a more representative ARH portfolio that holds $w_i \equiv N_i / \sum_i N_i$ in each stock, where i is a stock name and N is its number of Robinhood holders. It is of course unlikely that any particular investor held this portfolio. Instead, ARH should be viewed as a reasonable "consensus statistic" (among other viable ones), akin to the notion of a consensus forecast, as in Zarnowitz and Lambros (1987). It is a "crowd wisdom" portfolio.

If investors hold roughly equal-sized (or zero) positions proportional to their wealth, then the ARH portfolio would resemble a household[2]-equal-weighted portfolio. Unfortu-

[2] In the Barber–Odean data, accounts are identified as households. Thus, I adopt the same terminology, although the unit could well be an account or investor instead of a household. The ARH could also mimick a household value-weighted portfolio if the distribution of household wealth is sufficiently broad to distribute the weight across households for each stocks appropriately.

nately, data limitations prevent us from tracing RH investors' actual holdings. Fortunately, Brad Barber's and Terry Odean's generous sharing policy makes it possible to investigate an equivalent portfolio in the Barber and Odean (2000) data. Their data contain actual month-end portfolio holdings by account at another discount brokerage firm from 1991 to 1996. An ARH-equivalent portfolio showed a 97.1% correlation in investment weights with their household-equal-weighted portfolio. It had a rate-of-return time-series correlation net of the market of 98.6%.

The simplest way to characterize how the RH portfolio differs from a more (value-weighted or equal-weighted) market portfolio is to describe its correlates. The empirical evidence suggests that lagged stock trading volume can explain a large part of the ARH crowd portfolio's investment weights.[3] Trading volume includes itself a component related to retail investor participation, but the data further suggests that it is the retail investors who disproportionately end up owning these highly liquid stocks. A "quasi-robinhood" (QRH) portfolio, with 2/3 normalized share-trading volume and 1/3 normalized dollar-trading volume (both calculated over the previous year), has a 75% correlation with the ARH portfolio in investment weights. The rate of return time-series correlation net of the market is still over 90%. In the Barber–Odean data, the equivalent correlations were 75% and 86%. (With this high a correlation, the QRH portfolio can even stand in as a reasonable proxy for retail holdings for some purposes.)

Yet what is perhaps surprising is that the ARH portfolio did not underperform in the cross-section in this sample period, either. This is the case for a 0-factor model (i.e., returns above the risk-free rate), a net-of-the-market model, a 1-factor model (i.e., abnormal returns

[3] I can speculate that the remaining 40% relate to the visibility of products and stocks for my target investor group, as well as investor-specific idiosyncratic interests. Unfortunately, there are no readily available long time-series that would make it easy to measure these aspects. The appeal of these two volume-based proxies is their easy availability over a century.

adjusted for market-movements with beta), and a 5-factor-plus-momentum model (Fama and French (2015), Carhart (1997)), here dubbed the 6-factor model. The alphas of the ARH portfolio were positive, and despite the very short sample even statistically significant in the 6-factor model, with a respectable abnormal rate of return of 1.3% per month.

Robinhood investors were not collectively "cannon fodder," exploited by more sophisticated investors elsewhere. Good timing and good stock performance help to explain why RH investors did not attrition out but continued to pour in.

The volume-based QRH proxy portfolio could not perform as well as the ARH portfolio in the 2018–2020 sample. The QRH portfolio had positive 0-factor returns and 6-factor returns, but negative 1-factor returns. Though it is speculative to extrapolate the similarity of QRH and ARH (or their Barber–Odean equivalents) beyond the sample periods, it is interesting to note that the QRH had the same performance pattern from 1980 to 2019.

The ARH and QRH portfolio performances are not readily comparable to the return performances documented in most earlier studies of retail investors. This is because the analysis in my paper focuses on holding *levels* rather than changes or trades. The ARH performance reported here is more akin to the better-performing buy-and-hold retail investor benchmark mentioned in Barber and Odean (2000) than it is to their active traders. Moreover, the literature about the performance of retail *trades* is also not even clear in itself. Kaniel et al. (2012) and Kelley and Tetlock (2013) use proprietary data from the NYSE (2000–2003 and 2003–2007, respectively). They find that retail trades outperformed. Boehmer et al. (2020) find likewise using a novel metric for classifying (some) trades from 2010–2015 as retail trades. But Barber and Odean (2000), Grinblatt and Keloharju (2000), Barber and Odean (2002), Barber, Huang, et al. (2020) and others find that active trades by retail investors underperformed. Possible explanations for this discrepancy includes that performance could depend on the holding interval (Barber and Odean (2008)) or on the specific broker (Fong, Gallagher, and Lee (2014))—or it could be that stock returns have low external validity.

Other academic studies of Robinhood investors are also now emerging. Moss, Naughton, and Wang (2020) show that RH investors did not care much about socially responsible (ESG) investing, contrary to some experimental studies. Barber, Huang, et al. (2020) find that *herding-related* buying was not advantageous, losing as much as 5% over five days.[4] Moreover, they show that during RH outages, trading in stocks dropped by 0.7% (6% of retail activity), and even more for the 50 most popular RH stocks. Ozik, Sadka, and Chen (2020) show that RH investors traded more when COVID lockdowns took effect, effectively "grounding" more investors in front of their computers at home. Ben-David et al. (2020) identify RH investors as "sentiment driven" to classify ETFs by appeal to cost-conscious versus sentiment-driven investors.

Furthermore, the ARH investment weight is a monotonic transform of the "breadth of ownership" measure. While Chen, Hong, and Stein (2002) find that stocks held by fewer mutual funds subsequently underperformed, Nagel (2005) finds that this relationship disappeared in a sample that included five more years (according to Choi, Jin, and Yan (2013), who investigate *changes* in breadth of ownership). Again, even statistically significant return performance, carefully researched, often does not hold out of sample.

[4]A non-public J.P.Morgan research report by Cheng, Murphy, and Kolanovic (2020) studies RH changes. Unlike Barber, Huang, et al. (2020), they emphasize good timing of RH investors *on average*. Their finding that RH investors purchase strong winners and losers overlaps with the findings in Section II below.

I Some Background

A Robinhood

Wikipedia describes Robinhood Markets, Inc. as

> [an] American financial services company headquartered in Menlo Park, California. The company offers a mobile app and website that offer people the ability to invest in stocks, ETFs, and options through Robinhood Financial and crypto trading through Robinhood Crypto. Robinhood operates a website and mobile apps for iPhone, Apple Watch, and Android. The company has no storefront branches and operates entirely online without fees. Robinhood is a FINRA regulated broker-dealer, registered with the U.S. Securities and Exchange Commission, and is a member of the Securities Investor Protection Corporation. The company's main source of revenue comes from interest earned on customers' cash balances, selling order information to high-frequency traders (a practice for which SEC opened a probe into the company in September 2020) and margin lending. The company has 13 million users.

Although RH investors are individually quite small, collectively they are often seen as the "future of investing."

Presumably, with their payment for order flow, RH spreads the eliminated fixed-cost fee component into higher per-share variable costs, making it cheaper to buy and sell small positions but more expensive to buy and sell larger positions. However, the execution quality of Robinhood and its competitors is difficult to ascertain.[5]

[5] There is a lack of data on execution costs by all retail brokers in the market. A federal statute (related to price manipulation) that criminalizes the probing of execution quality using sample round-trip trades makes sure it stays this way.

RH's rapid growth led other brokers to abandon brokerage fees by October 2019. It was also reputed to have helped induce the merger between Charles Schwab and Ameritrade. RH also had its own fair share of controversies, relating to service outages, cryptocurrency, banking, payment for order flow, a security breach, and even the suicide of one of its investors.

B Robintrack

Robintrack.net (RT) was created in 2018. For about three years, RT ran scripts to download the data made publicly available on RH's API. RH terminated this public API in August 2020 and RT froze its operations. By this time, the database had accumulated into 3.5GB of data. After removing repeated intra-hour observations and unchanging holdings, it contains about 12 million ticker–hour observations. For each stock, I extracted the last UTC observation for each day.[6]

This resulted in 5,777,002 RH ticker–day observations from 802 unique days and 8,597 useful tickers.[7] Of the 8,560 RH tickers, 8,387 tickers were matchable to CRSP. Of these, 3,834 were ordinary equity (CRSP sharecode 10 or sharecode 11). My paper pertains only to this specific ex-ante identifiable investment universe.

Some tickers do not appear at all, others appear late in the RT data. Early versions of the script probably omitted dual-class tickers ending with *.A* or *.B*, most prominently Berkshire Hathaway. RT remedied this with an upgrade issued on January 16, 2020.[8]

[6] The NYSE closes at 4:30pm EDT, which is 22:20 or 23:30 UTC.

[7] The RT data is *not* professionally maintained and cleaned, thus requiring extra care. It contained some incorrect tickers, such as _OUT, _PRN, MTL-, PKD∼ (and its sibling PKD), which I hand-removed.

[8] Thus, BRK.B suddenly appeared with 38,023 users (and BRK.A with 134 users). (Figure 5 shows that BRK.A was right on the fitted line on June 30, 2020.) Other noteworthy dual-class examples that also appeared on January 16, 2020 are Royal-Shell Dutch and Lions Gate Entertainment.

Nevertheless, some stocks are never found in the RT dataset for reasons unknown, most prominently CELG (Celgene) and TWX (Time-Warner).

The RT data begin on May 5, 2018. Over time, the number of RH investors increased, and given the law-of-large-numbers, presumably so did the reliability of the number of RH investors holding individual stocks. My paper analyzes the sample from June 1, 2018 to September 30, 2020 (the last day of my CRSP data set). There were 546 valid CRSP trading days. RH itself suffered some systemwide outages on March 2, 2020 and March 9, 2020. The RT script failed to run on August 9, 2018, on January 24–29, 2019 (4 days), and January 7–15, 2020 (7 days). The last RT outage followed the dual-class script update.

C Caveats

It is important to offer appropriate cautions before the analysis. The first major caution relates to external validity.

The behavior of RH investors may or may not be representative of the behavior of other retail investors in 2020—much less of the behavior of retail investors in another U.S. brokerage firm from 30 years ago, Finnish investors from 25 years ago, or retail investors one decade into the future.

The same can be said for the unique period studied here. It includes a transition to zero-fee brokerages, the COVID 2020 bear market and recession, and the subsequent bull market. Extreme events (e.g., 2020, just just like 1929, 1987, 2000, or 2008) are by nature near-singular events with unique aspects. However, by virtue of being extreme events, they can also provide us with a better glimpse into investor behavior—during normal and stressed times—than what is otherwise possible.

The reader must make her own subjective assessment as to whether the results have external validity beyond what is reported here. Equivalent concerns about external validity apply to most other empirical finance studies. From my own perspective, the evidence below has plausibly good external validity when it comes to investment behavior, some of which could be verified in the Barber–Odean data. In contrast, the RH investment performance is likely less extrapolatable, like all return performance. Nevertheless, historically realized return performance remains interesting in this context, because it can help explain why RH investors have not been attritioning out but have been continuing to pile in.

The second major caution relates to the limited information available in Robintrack. Without access to the disaggregated investment holdings and transactions of individual RH investors, it is possible only to investigate aggregate and relative stock-specific holding (and holding changes). This obscuration of the data leads to two more concerns.

When investigating changes in holdings, multiple stock holdings could increase suddenly when investors transfer brokerage accounts from elsewhere to RH. However, transferring assets from another brokerage firm to RH does not seem to be common. My repeated email interactions suggest that my customer service representative did not even understand my question about how to do this. Instead, she could only repeatedly suggest funding my RH account by linking it to my bank account.[9]

RH gives each investor one free randomly-chosen share upon signup or referral. Among these new investors, 2% are "winners" because they receive one share drawn from six stocks priced above $10 and explicitly named on RH's bonus page. The shares given to the other

[9] It is also not possible to transfer fixed amounts of cash (e.g., via PayPal or check) to Robinhood. Thus, to fund their accounts, millions of RH investors handed their user credentials (*including passwords*) for their bank accounts to an intermediary named "Plaid," which then linked RH to their bank accounts. If Plaid were to be hacked, banks would assume no liability for withdrawn funds.

98% are impossible to ascertain.[10] Although investors could sell their initial share—and even without commissions and fees—it is also likely that many investors simply hold on to their share. With some such holdings representing only one single share, they could seem more important than they are. Unfortunately, this is impossible to investigate or to control for.

The initial share and referral bonuses are a source of noise in all studies that use RH data. They are particularly concerning when investigating the causes and effects of *changes* in *individual* stock holdings—issues tangentially covered in Section II but not a primary concern of my paper. These bonuses are somewhat less problematic when investigating *aggregate* changes in holdings in Section III. The reader should simply keep in mind that the source of increased holdings in the stock market could be new investors entering rather than existing investors adding positions. The bonuses could also add noise when investigating the ARH aggregated portfolio-level holdings (as in Section IV), but the noise would be less severe than when investigating changes. In all case, the reader should be clear that investment performance could include a component that was due to selection by random luck (and non-selling) rather than deliberate choice by investors.

In sum, the number of holdings can be a reasonable but noisy proxy for investments. An absence of findings could have been interpreted as insufficient power in the presence of noise, but statistical power seems not be a problem. Moreover, the main portfolio investment weight findings are robust in that they also hold in the Barber–Odean data set, where there are no such noise concerns and the data makes it possible to trace more detailed information.

[10] A survey of past recipients confirms that the selections did not adhere to a literal reading of the description in the bonus offer. That is, these shares were not drawn from the three highest capitalized stocks with prices below $10. While the exact mechanisms should not matter to RH investors, it could matter in some academic studies. I suspect that Robinhood merely reassigns some random share just sold by another investor to the new investor, thereby saving all external costs. If this is correct, the sale of one larger position could splinter into more holders rather than fewer–though still in line with new investors signing up.

II Stock-Specific Responses To Large Returns

This section begins by examining whether firm-specific stock returns can explain subsequent *changes* in RH holdings. Grinblatt and Keloharju (2001) show that Finnish investors from 1994 to 1997 purchased on either up or down movements, and Barber and Odean (2008) show that U.S. investors did likewise from 1991 to 1999. However, it is not a foregone conclusion that RH investors act alike. It would not have been impossible for RH investors to behave differently. Neither the time period nor the types of investors overlap. The RH sample consists of smaller investors, 25 years later, perhaps even wiser after the 2000 Tech Collapse. The sample also includes the 2020 COVID experience—the most severe contraction of the economy since the Great Depression, all in the midst of a sharp stock market decline followed by a sharp bull stock market.

To the extent that the behavior of these different investors at RH is interesting in itself, empirical evidence is required to learn whether they behaved similarly or differently. This section shows that they behaved similarly. RH investors' preference for individual stocks with large price changes is also useful background information when assessing whether the evidence in the next section (on aggregate purchasing patterns) generally fits with their trading patterns.

A Some Extreme Holding Changes

Before proceeding to the statistical evidence, Tables 1 and 2 provide an intuitive characterization. They describe the most extreme cases of changes in the ARH investment weight, i.e., in a portfolio formed in accordance with the number of RH investors holding each stock (as already described in the introduction). These weights will be investigated in more detail in Section IV.

[Insert Table 1 here: **Extreme 1-Day Increases in RH Holdings**]

Table 1 lists stocks with unusual one-day increases in RH investor interest. The common feature seems to be highly unusual one-day stock price increases or decreases. Some events also involve stock splits. Note that stock splits do not mechanically change the number of investors in the stock.

[Insert Table 2 here: **Extreme 1-Day Decreases in RH Holdings**]

Table 2 lists stocks with unusual one-day decreases in RH investor interest. There are again some rather stark stock price changes, tilting more towards losses. Sounding somewhat trite, IGC investors seem to have decided to realize their profits after stark price increases. However, the stock price patterns in these extreme declining-RH interest cases was not as strong.

B Purchasing Individual Stocks on Large Price Changes

[Insert Figure 1 here: **RH Holding Changes by Previous Day Net-of-Market Rate of Return**]

Figure 1 shows more systematically that RH investors purchased stocks when their prices increased or decreased greatly. This could be due to their attraction of attention in the Barber and Odean (2008) sense and/or sensation in the Grinblatt and Keloharju (2001) sense. I first categorized all trading days by their rates of return net of the market (both from CRSP). The plots then tabulate the RH change statistics on the following trading day.

No attempt is made to distinguish between causal and correlative-only associations. It could be that other news both induced first an instant stock price change followed by later investor trades (possibly ignorant of the recent price change itself). The time precedence however assures that these later RH trades themselves would not have caused the stock return in the first place, as in Barber, Odean, and Zhu (2008).

The top plot in Figure 1 tabulates the fraction of stocks that experienced increases in their RH holdings versus decreases in their RH holdings on each day. It shows that when stocks either increased or decreased by about 20% (in logs) in one day, the number of RH investors increased on the following day in about 3 of 5 cases (30% more buys than sells). Not shown, this is only about one-third of the effect, because the number also increased in about 4 out of 5 cases on the day of the large price change itself.[11] These strong increases in RH holdings contrast with small decreases after stock–days with small nondescript returns. The plot also shows (in lighter colors) lines based only on pre-2020 and post-2020 data. The observed pattern was stable over time. If anything, it has become stronger.

The bottom figure tabulates ARH portfolio weight changes. This takes into account (a) that an increase from 50 to 51 holders is not the same as an increase from 1 to 100 holders, and (b) that other stocks may also have experienced changes on the same days. The response on the day after is still a U-shape, but the plot shows that the increase in RH investors was stronger on the return upside than on the return downside. Again, not shown, an equivalent but even stronger effect appears on the day of the large rate of return itself. Together, the two plots suggest that increases of interest on the downside often occurred among smaller stocks, where just a few net purchasers would have increased the total number of RH investors.

[11] Intra-day investigations show that RH investors respond to rather than anticipate large price movements. Because firm-specific purchases and sales are not the focus of my paper, this intraday evidence is omitted. It would also not seem plausible that RH investors would have much better intelligence than other investors. The first-order source of the same-day correlation "must" logically have been subsequent trading rather than preceding knowledge.

In sum, the evidence suggests that RH investors also purchased stocks after large price movements like their counterparts 25 years earlier. This effect is weaker for large stock price decreases than for large stock price increases.

III Aggregate Holdings and the March 2020 COVID Decline

Retail investors could behave differently in stark or prolonged market-wide downturns. They could start to panic, or they could face margin calls. Both Grinblatt and Keloharju (2001) and Barber and Odean (2008) were limited in their ability to investigate such behavior. There simply was no large decline in the Grinblatt–Keloharju sample, and the biggest decline in the Barber–Odean sample was only 15% (July 1998). In contrast, the 2018–2020 sample contains the COVID bust and boom. After reaching a high of 3,386 on February 19, 2020, and falling back to 3,130 on March 4, 2020, the S&P 500 fell to as low as 2,237 on March 23, 2020. This was a 33% decline from its high a month earlier, with reasonable expectations of a calamitous economic depression caused by COVID looming ahead. Remarkably and perhaps unexpectedly, although the economic depression did materialize, the stock market recovered to 3,000 by the end of May and proceeded to reach all-time highs (3,662 on December 1, 2020).

[Insert Figure 2 here: **Sum Total RH Holdings and Stock Market Performance, 2018-2020**]

Interpreting the aggregate time-series behavior in response to stock returns visually is mildly complicated by the fact that Robinhood experienced strong investor growth throughout the entire sample period. Figure 2 shows a full-sample tally of the number of holdings.[12] The sum total of RH holdings grew steadily 0.22% per trading day (77%

[12] A smaller spike in January hints at tax-related, bonus-related, or New-Year-resolution related purchases. The plot in Appendix Figure 5 is a closeup view.

per year) from mid-2018 to the end of 2019, then dramatically accelerated to a peak growth rate of about 3% per trading day around the end of March 2020, and finally slowly decelerated back to (about) its original 0.22% growth rate. Thus, the steepest RH growth was roughly contemporaneous with the COVID onset and stark decline in the stock market. Indeed, Ozik, Sadka, and Chen (2020) even suggest that the COVID lockdown itself may have contributed to this acceleration.

[Insert Figure 3 here: **2018-2020 RH Systematic Contrarianism By Horizon**]

Figure 3 presents the same information but for different horizons in an x-y graph. It plots the performance of the S&P 500 and the contemporaneous percent change in RH sum total holdings. The measuring intervals for both variables are equally long and consecutive intervals are overlapping. The figure shows that over horizons from 1 day to 1 month, both large decreases and increases in the S&P 500 associated with large contemporaneous increases in the sum total number of holdings by RH investors.

Although one should not attribute the inflow of RH investors to deliberate planning, one can ask how well RH investors happened to have timed entry. The lowest number of holdings was 4.3 million on the first day of my main sample (June 1, 2018), the highest was 43.1 million on the last day of my sample (August 13, 2020). Imagine that every holding represented an equal investment, that funds not invested in RH holdings were in cash, and that funds allocated to RH were in the S&P 500. For convenience, consider the rate of return on cash to be zero.

With these assumptions, on June 1, 2018, RH investors would have held 13% of their funds in the market and 87% in cash. Over the following 545 trading days, their equity allocation would have been only 35% on average, reaching 100% only on the final day.

The investment-weighted rate of return for such investors, based on (one-day lagged) holdings, would have been 3.57 basis points (bp) per day (19.6% overall). Investors who always held the market would have earned 5.14 bp per day (28% overall). However, the standard deviation of RH investors would have been only 0.76% per day, while the standard deviation of the market would have been 1.6% per day. Thus, the Sharpe ratio of RH investors would have happened to be higher than that of the stock market overall. Though unlikely to be deliberate, their macro investment timing turned out to be lucky.

[Insert Table 3 here: **Daily Percent Changes in the Growth Rate of RH Holdings**]

Table 3 investigates the association between daily percentage changes in the S&P 500 and daily percentage changes in the aggregate number of RH holdings. The two left regressions use the entire sample. The two right regressions begin in February 2020 (thereby omitting the January 2020 RT script update). The S&P 500 return has to compete with a constant and a battery of lagged auto-coefficients, which attribute various trends to unrelated factors. These should also capture the acceleration of RH holdings at the onset of the COVID crisis.

The estimated coefficients on S&P 500 stock returns suggest a first spike in RH holding changes on the day of and one day after the stock market increased or decreased. This mirrors their behavior after individual stock price increases or decreases, as described in the previous section. This timing suggests that some RH investors learned about strong market movements towards the end of the day and added further holdings via their existing (margin) purchasing balances on the following day.

More intriguingly, a second investment spike occurred about 4 to 5 days later—roughly the time required to complete a bank transfer. This second spike of about 9% on the bear side suggests that the 33% COVID market drop would have increased the aggregate holdings of RH investors by about 3%. This increase would have likely been funded by dollars previously held in cash or savings accounts and would now have flowed into the riskier equity markets.

Note that although RH investors' response to stock market changes is quite respectable and statistically significant, these stock market changes can explain only a small sliver of the nearly tenfold increase in RH holdings. Depending on the column, the coefficients on either positive or negative market movements only add up to about 0.1 to 0.2. Thus, even the 30% increase in the overall stock market during the sample period could not have been a major driver of RH holding increases and/or signups.

In sum, just as strong price increases or decreases can predict additional RH holdings of individual stocks in the cross-section, strongly positive or strongly negative overall market movements can also predict increases in RH positions in the time-series. This evidence suggests that RH investors did not retreat from the stock market during its starkest decline. Instead, it appears that they played a small but active market-stabilizing role during the COVID crash. (They are not necessarily a stabilizing force in general, if only because they also buy aggressively in bull markets.) Glossner et al. (2020) investigate the selling behavior of mutual funds and hedge funds and the purchasing behavior of RH investors and reach a similar conclusion.

In this case (as in the other U.S. stock market crashes in our lifetimes), holding on or increasing one's market exposure after a market bust would have paid off handsomely in the subsequent stock-market boom.

IV The ARH Portfolio Perspective

In the aggregate, RH investors experienced fortunate timing for their entry into stock market investing. This raises the question of how their holdings performed in the cross-section. I define the ARH crowd portfolio as

$$w_{i,t}^{\text{ARH}} \equiv \frac{N_{i,t}}{\sum_i N_{i,t}} \ , \tag{1}$$

where i is a stock index and t is a day index. The ARH portfolio invests more when more investors are holding a stock. For example, if there are twice as many owners of stock A compared to stock B, the weight of A in the ARH portfolio is twice that of B. Note that the price of the stock is irrelevant. Thus, an investor with any number of shares in a \$1 stock and any number of shares in a \$100 stock is considered to have placed 50% weight on each. The weight $w_{i,t}^{\text{ARH}}$ is thus more representative of two investors with 100 shares in the former and 1 share in the latter (i.e., investing \$100 in each stock) than of two investors with 50 shares in each (i.e., investing \$50 in the former and \$5,000 in the latter).

ARH is unlikely to be a good approximation for shares in a household-value-weighted portfolio, given the heterogeneity in wealth and holdings. However, as already mentioned, ARH could plausibly proxy for a household-equal-weighted portfolio, and it is possible to investigate an equivalent portfolio in the Barber and Odean (2000) data. Their data contains actual month-end portfolio holdings by account.

Panel A in Appendix Table 10 shows that an ARH-equivalent portfolio (constructed based only on number of investors in each stock and analogously named ABO) had a 97.1% correlation in investment weights and a 98.6% correlation in rates of return (net of the market) with a Barber–Odean *household-equal-weighted* portfolio. This high a correlation suggests that the ARH portfolio could plausibly serve as a proxy for the household-equal-weighted portfolio of RH investors, too—although there is no guarantee that correlations from 30 years ago in a different sample of investors still apply to RH investors today. Panel B shows that the correlation of ABO with the *household-value-weighted* portfolio was not as strong, reaching only 77.8% rather than 97.1%.

The ARH portfolio is not the only possible crowd portfolio that could be considered. One of its drawbacks is that when a stock increases in value, its tilt does not increase in the ARH portfolio across rebalancing intervals. (To address this concern, the tables below also show results for longer holding periods.) An alternative crowd portfolio would be one in which each investor (holding) represents an equal number of shares. In this case, $w'_{i,t} \equiv (n_{i,t} \cdot P_{i,t})/(\sum_i n_{i,t} \cdot P_{i,t})$, where P_i is the prevailing stock price. The first drawback of this alternative portfolio is that any variable correlated with price (such as market cap, dollar trading volume, or simply price itself) becomes nearly mechanically correlated with this portfolio's investment weights. That is, the portfolio investment weights would no longer measure only information obtained from RH. The second drawback is apparent also in Table 10. The "ABO×P" portfolio investment weight correlation is lower (than that of the ABO portfolio) with either the household-value weighted or the equal-weighted portfolio in the Barber–Odean data.

In sum, the ARH portfolio considered in my paper is a feasible crowd-wisdom portfolios. Its investment weights summarize the RH crowd participation in one particular way, most likely similar but not identical to the investment weights in a household-equal-weighted portfolio.

A Odd but Unimportant Holdings

[Insert Table 4 here: **Highest ARH vs. VWMKT Log-Investment-Rank Differences on 2019/12/31 or 2020/06/30**]

The behavior of RH investors is commonly ridiculed. Indeed, RH investors overweighted some rather unusual portfolio positions. For example, the ARH weight of India-Cannabis (IGC) was much higher than its value-weighted market cap-based weight (from CRSP). Table 4 shows that IGC ranked 27th in the ARH holdings in 2019 with 0.59% of the ARH portfolio. *Yahoo!Finance* describes this 50-employee company as follows:

> *India Globalization Capital, Inc. purchases and resells physical infrastructure commodities. The company operates through two segments, Infrastructure Business, and Life Sciences. It buys and sells infrastructure commodities, such as steel, wooden doors, marble, and tiles; rents heavy construction equipment, including motor grader, transit mixers and rollers; and undertakes highway construction contracts. The company also develops cannabinoid-based products and therapies, such as Hyalolex for the treatment of patients from anxiety, agitation, dementia, depression, and sleep disorder diseases; and Serosapse for the treatment of Parkinson's disease. In addition, it offers offer extraction, distillation, tolling, and white labeling services under the Holi Hemp brand; and hemp crude extracts, hemp isolates, and hemp distillates. The company operates in the United States, India, and Hong Kong. India Globalization Capital, Inc. was founded in 2005 and is based in Potomac, Maryland.*

It is difficult to think of a rational portfolio in which IGC would deserve an investment weight similar to that of J.P. Morgan.

Although not shown in the table, other cannabis stocks also attracted unusual interest from RH investors. (The RH mobile interface even has a special button dedicated to displaying the most popular cannabis stocks.) As already noted in the introduction, at the end of January 2019, Aurora Cannabis (ACB) was briefly the most popular stock on RH.

Moreover, Table 4 shows that RH investors also had a relative holding (and trading) preference for certain oil & gas-related exploration and biopharmaceutical-related companies. The common denominator seems to be that these stocks tend to have high idiosyncratic outcome risk.

In sum, it is easy to spin a tale in which RH investors fit the stereotype of the unsophisticated gamblers who buy on impulse, and earn low returns—being taken advantage of by more sophisticated professional traders. Barber, Huang, et al. (2020) even show that during *a few extreme herding episodes*, their trades were so ill-timed that some trades lost 5% of their investments (although Cheng, Murphy, and Kolanovic (2020) report good timing *on average*).

B Important Holdings

However, this cannon-fodder narrative is incomplete to the point of being misleading. RH investors were greatly overrepresented in some rather odd stocks (as in IGC) and suffered from all sorts of behavioral and perhaps sometimes harmful patterns when timing their buys and sells. However, this does not mean that the most important holdings in their consensus portfolio were in these rather odd stocks. Put differently, the odd holdings described in Table 4—though possibly of real and distorting consequence to a number of affected companies—were not the rule but the exception. From the perspective of the overall ARH portfolio, cannabis stocks can be described as interesting but small experience or curiosity holdings.[13]

[Insert Figure 4 here: **Snapshot ARH Weights by Log-Rank of Market Cap**]

Figure 4 provides a graphical perspective of ARH portfolio holdings for two snapshots, one at the end of 2018, the other towards the end of the sample in mid-2020. The blue line is a smoothed version of the perfectly monotonically declining relation between the log market-cap rank and its weight in the market cap-weighted portfolio. The black line is a smoothed version of the relation between the log market-cap rank and the weight in the ARH portfolio.

Although IGC was perhaps the strangest popular holding in Table 4, it was not even particularly noteworthy in the overall portfolio. After all, even at its height, IGC still represented only 0.5% of the portfolio, leaving 99.5% for other holdings. Many other stalwart stocks represented more than twice IGC's weight. The other outliers from Table 4 are not even noticeable in the cloud of other holdings.

This does not mean that the ARH portfolio mimicked the market cap-value weighted portfolio. For example, the top plot for December 31, 2018 shows that Ford (F) was nearly as popular as Apple (AAPL) and Microsoft (MSFT), with 3.5% versus 3.8% and 2.9% respectively. Yet Ford's market cap-based weight was much lower, with 0.13% versus 3.3% and 3.4%, respectively. Other popular stocks were AMD, Fitbit, GoPro, Netflix, Snapchat—firms with products familiar to computer-savvy Millennials.[14]

[13] My analysis understates the "sanity" of ARH, because it excludes many better diversified ETF portfolios (with CRSP share codes other than 10 or 11). These are also commonly held by RH investors but are not considered in my study. Like most other studies of retail customers, I also have no data on their external investments.

[14] It seems unlikely that Robinhood attracts the same lower socioeconomic clienteles that were studied in Kumar (2009). However, they do seem to share some of their gambling predilections.

Comparing the top to the bottom plot shows that the (blue) market-cap weighted curve steepened in the sample period, with AAPL reaching a value of $1.6 trillion and representing about 5% of the overall stock market. In contrast, the slope of the black RH curve for ARH weight by market cap remained roughly unchanged. Although the ARH portfolio also invested strongly in AAPL (with about 2% weight), it did so less aggressively than the value-weighted market by mid-2020. Instead, RH investors overweighted Disney, GE, Ford, and airline stocks. (Remarkably, they did not hold unusually large investments in Tesla, perhaps the most surprising gainer during the COVID crisis. This suggests that retail investors were not particularly responsible for Tesla's quintupling.) A fair characterization is that although retail investors had loved "new-economy" stocks in mid-2018, their portfolio had tilted more towards fallen "old-economy" stocks by mid-2020.

[Insert Table 5 here: **ARH Investment Weights *Far Above* VWMKT Investment Weights**]

Table 5 lists the largest holdings by RH-portfolio investment weight. With data for both snapshots for a given stock, it provides a perspective on the evolution of these holdings. A stock can see increases both in its ranking relative to other stocks and in its market cap-relative weight in the RH portfolio if

1. it is *more* actively purchased by (new) investors *relative* to other stocks, and
2. its price (and thus its weight in the value-weighted market portfolio) decreases relative to other stocks.

The table shows instances of both. For example, RH investors adored American Airlines (AAL), although it had dropped from a high of about $50 per share in late 2018 to about $10 per share in mid-2020 (reducing its weight in the value-weighted CRSP index from about

0.06% to 0.02%). The 7,300 original holders in 2018 grew to 654,611 holders in 2020, far beyond the average 360% increase in the total number of RH holdings. American Airlines' weight in the ARH portfolio thus increased from 0.12% to 2.39%. Facebook (FB) had good stock market performance, raising its weight in the value-weighted market from 1.34% to 1.78%. But it fell out of relative favor with RH investors, because RH holdings increased only by 40% rather than by the 360%. PLUG (a hydrogen fuel researcher) benefitted from both a strong rate-of-return performance and from increased interest.

In sum, even though some of the investments in odd and small experience stocks were eye-popping, these positions represented only a small part of the RH crowd portfolio. They were a storm in a teacup. The big picture was in larger stocks, typically more familiar to and focused on retail consumers (especially Millennials).

C Mimicking The ARH Crowd Portfolio

To explain the nature of the ARH portfolio, it is useful to describe its correlative determinants.[15] A few issues must be kept in mind when doing so. First, it is more important for a prediction of investment weights to explain the top 50 holdings rather than the bottom 3,000 holdings. These 50 top holdings are by-and-large not odd experience micro-stocks like IGC. Mispredicting the weights of cannabis stock is forgivable; mispredicting the weight of AAPL is not. Second, like most investment portfolios (and especially aggregated ones), the ARH portfolio exhibits strong hysteresis. Figure 4 and Table 5 have shown that many investment weights are stable over more than a year. Thus, short-term variables (like recent rates of return) are unlikely to help explain much of the investment weights. Third, it is

[15] (Market-wide relative) trading volume in individual stocks is not exogenous. There is no empirical evidence that an engineered deliberate exogenous shock to trading volume (whatever this might be for an endogenous variable) would change RH holdings.

not useful to attempt to explain changes in ARH weights *for this purpose*, because we have no earlier ARH portfolio holdings on which we could recalibrate predicted ARH portfolios weights. Fourth, we do not primarily want to explain the ARH weights (which may well be over-fitted), but the difference in rates of return between the ARH portfolio and other well-known factors (which were deliberately ignored in the fitting).[16]

With 1.7 million matched ticker–day investment weight observations, it was feasible to start with minimal theory and try to disentangle similar variables empirically. A 50-variable "kitchen-sink" regression—containing such variables as IPO date, alphabetic index of name and ticker, market caps, minimum or maximum to highs and lows, share prices and returns, index membership, financial statement variables, and various holding periods and transformations—could achieve a correlation between predicted and actual weights in the ARH portfolio of about 80%.[17]

The highest single-variable investment weight correlation was observed for a portfolio constructed using only *share-trading volume* over the previous 12 months. This portfolio had a 70% weight correlation with ARH, about 10% less than the kitchen sink. The next-highest weight correlation was for *dollar-trading volume*, even including share-trading volume as a predictor. Combining the two trading volume variables yielded an investment weight correlation that was only about 5% lower than the full kitchen-sink model. Moreover, these two volume-based variables are also plausible measures of retail *trading*, though not

[16]The attention measures in Lee and Ready (1991), Kelley and Tetlock (2013), and Boehmer et al. (2020) track retail investor order *flow*. They are likely to be related more to *changes* in investment weights than to investment portfolio *levels*. But their main drawback is that their variables are likely to remain boutique variables because they are not easy to obtain and replicate.

[17]I can speculate that the remaining $(1-.8^2)\approx 40\%$ unexplained variation in investment weights relates to stock attributes for which there are no readily available (long-term) comprehensive proxies. These would be variables such as retail customers' excitement about products, measures of the share of consumer expenditures spent on these companies, their brand values and advertising, the excitement and promise of new technologies, and/or perhaps even their products' recent performance. Such variables could perhaps help explain why RH investors preferred Delta and American Airlines over United Airlines, Ford over General Motors, Disney more in 2020 than in 2018, or Facebook more in 2018 than in 2020. This investigation is left to future research.

necessarily of retail *holdings*. (It is not a foregone conclusion that retail investors would be the ones ending up with high-trading volume stocks.) Neither the rate of return over the last year, nor the volatility, nor the price peaks or troughs added much economic explanatory power to the model.

[Insert Table 6 here: **Correlations of QRH with ARH**]

In detail, the two trading volume metrics are combined by first transforming each variable into a portfolio weight ($w_i(v_i) \equiv v_i / \sum_i v_i$). Panel A of Table 6 shows that both individual metrics alone are not as good in explaining the ARH weights as their weighted average (QRH). This average, in rough accordance with estimated coefficients, assigns twice the weight on share volume as on dollar-trading volume.[18,19]

As with the kitchen-sink model, the prediction considered only the investment weight fit and ignored the rate-of-return fit. Panel B shows the resulting contemporaneous rate-of-return correlations of the ARH and the QRH portfolios in the time-series. Their raw return correlation is 98%. However, this contains shared stock market variation. After taking out the five Fama–French factors plus momentum with a linear 6-Factor Model, the correlation between the residual ARH return and the residual QRH return remains a respectable 80%.

In Appendix Table 10, Panels B and C repeat these analyses in the Barber–Odean data. The association of the QRH-equivalent QBO investment weights with the ARH-equivalent ABO investment weights is almost identical to the association of the QRH investment weights with the ARH investment weights. Instead of a correlation of 76% between ARH and QRH,

[18] The empirical coefficients are robust and not greatly sample-specific. (An earlier draft used out-of-sample weights and came to similar conclusions.) The 2/3 vs 1/3 combination predicted better than the 50-50 combination, but the two variables are sufficiently correlated that a 50-50 combination would have been acceptable, too.

[19] The same portfolio weight normalization has to be applied to the (2/3)/(1/3) a second time in order to maintain a total investment weight of 100% when future returns can be missing.

the ABO–QBO correlation was 75%. Similarly, instead of a rate of return correlation net of the market of 88% between ARH and QRH, the ABO–QBO return correlation was 86%.[20]

In sum, relative to other known factor portfolios, the RH portfolio (and perhaps retail holdings in general) can be described as tilting heavily towards stock that have had high trading volume over the last twelve months.

V Holding Portfolio Return Performance

A The Performance of the ARH Crowd Consensus Portfolio

[Insert Table 7 here: **Return Performance of the ARH Crowd Portfolio**]

Table 7 analyzes the predictive returns performance of the ARH portfolio using the familiar methods of Fama and French (2015). The ARH portfolio was investible in time—the holdings were downloadable from RT or the RH API. Again, this "crowd wisdom" portfolio should not be viewed as representative of the portfolios of individual investors. Indeed, with about 40 million holdings as of mid-2020, and given its base of about 13 million investors, the average RH investor only held about three positions, not three-thousand!

Panel A of Table 7 shows that the average daily performance of the ARH portfolio was a positive 10 bp per day on the 0-Factor model, i.e., net of the prevailing risk-free rate (from Ibbotson via Ken French's website). This abnormal performance declines to about 5 bp on the 1-Factor model, i.e., when the (ex-post realized) market exposure of 1.13 is taken into account. The abnormal performance increases back to 6.5 bp on the 6-Factor model. (Not shown, it was similarly positive for the 5-factor model.) Not surprisingly, because the ARH

[20]The equivalent rate of return correlation of QBO with a household-equal-weighted portfolio is still 81% when returns are net of the value-weighted market and 92% when they are net of the equal-weighted market.

portfolio moves slowly, its performance is insensitive to delay. With a 5-day delay before investing, the performance deteriorates only a little, from an alpha of 10.4 bp/day to an alpha of 9.7 bp/day.

Panel B shifts to monthly returns. This changes the rebalancing interval on both the factors and the ARH portfolio. The performance of the ARH portfolio improves modestly, offering an alpha of 1.3% per month against the 6-factor model with a T-statistic of 2.46. Again, the portfolio is persistent enough that even a three-month delay reduces this alpha only to 1.2% (with a T-statistic of 2.43).

Panel C calculates the rates of return on two portfolios: one formed at the end of June 2018 and the other at the end of June 2019, both held for one year.[21] The ARH portfolio avoided the negative returns of SMB, HML, and CMA.

In sum, the ARH portfolio performed surprisingly well in the cross-section. Moreover, these performance regressions assume equal investments in different periods. They ignore the effects of time-varying RH investor entry and exit into the stock market. The regressions thus understate the performance due to RH investors having entered the stock market during a period of rising stock prices.

Nevertheless, caution is advisable. Although the alphas and their statistical significances are high, investment performance—whether published in prestigious finance journals or not—is in general a notoriously poor predictor of future investment performance. It seems prudent to bear in mind that the solid finding here is not that RH investors can collectively beat the market, but that they were not cannon fodder for more sophisticated investors, destined to attrition out quickly. Instead, RH investors continued pouring in.

[21] The factors are cumulated, because I did not have access to the long and short legs of the RMW and CMA portfolio for calculating mid-year compound rates of return. However, this should matter little.

[Insert Table 8 here: **Return Performance of the QRH Proxy Portfolio**]

Table 8 investigates the performance of the QRH portfolio in the same 2018–2020 sample. (Recall that an equivalent QBO portfolio was also a good predictor of the household-equal-weighted portfolio in the Barber–Odean data.) The QRH performance in the 2018–2020 sample is about 4 bp/day lower than that of the ARH performance in all benchmark models. On longer rebalancing intervals, the 0-Factor and 6-Factor alphas remain positive, but the the 1-Factor alpha turns negative.

Panel C explains the ARH portfolio performance including QRH as an additional "volume factor." The QRH volume factor can subsume most of the influence of the more conventional factors. The alpha reduction from 1.29% per month to 0.67% per month suggests that about half of ARH's performance is related to trading volume, the other half is unidentified skill or luck.[22] Although trading volume was an important ingredient in the RH holdings and contributed to the positive alpha on the 0-Factor and 6-Factor models, the RH crowd simply knew better how to invest than this naïve two-attribute QRH model.

[Insert Table 9 here: **Extended Return Performance of the QRH Proxy Portfolio After 1980**]

Table 9 extends the QRH-based trading volume strategy back to 1980. Though investible (and interpretable as merely the returns to a volume-based strategy), the predicted returns can be viewed speculatively as standins to mimick the Robinhood or Barber–Odean investors—akin to the first stage of an IV regression. The QRH portfolio would have achieved, by and large, a similar performance from 1980 to 2020 as it did from 2018 to 2020. It would have had positive 0-Factor and 6-Factor alpha but negative 1-Factor alpha.

[22]It is possible to improve the predictive performance of QRH by taking 6-Factor factor loadings into account. A modestly better proxy for the ARH investment weight would be $w_{\text{QRH}} \approx 0.15 \times \text{HML} - 0.15 \times \text{UMD} - 0.35 \times \text{CMA}$. The 40-year inference in the next table remains similar under this measure.

VI Conclusion

RH investors not only increased their relative holdings in individual stocks when their stock prices increased or decreased greatly, but also increased their overall holdings dyrubg the market-wide 33% COVID drop in March 2020. They did not panic. They added more positions four days after market increases or decreases, suggesting that they transferred funding to their RH accounts in response to volatility. In March 2020, they were thus a (small) stabilizing force. Given the subsequent rise in the stock market, their timing and steadfastness contributed to their good portfolio returns—as did their general increase in participation from 2018 to 2020.

Some of their holdings seem bizarre. They fell in love with some obscure experience stocks, such as cannabis stocks. Nevertheless, on the whole, the ARH crowd consensus portfolio (itself likely similar to an equal-investor-weighted portfolio) was not greatly tilted toward these experience stocks. Instead, a better description is that RH investors tilted mostly towards stocks with above-average trading volume over the previous twelve months. (This association is even strong enough to allow the use of a trading volume–derived metric as a proxy for retail holdings in some circumstances.) Visual inspection further suggests a preference for stocks of firms with products that appealed to Millennials and lately (i.e., as of August 2000) familiar fallen old-economy stalwarts like airline companies.

From the mid-2018s to the mid-2020s, the RH consensus portfolio performed well in the cross-section, earning positive alphas with respect to the risk-free rate, the market-model, and the Fama–French 5-factor plus momentum model. Past performance is no guarantee of future performance, but their good performance shows that more sophisticated investors did not take advantage of RH investors and helps to explain why RH investors did not attrition out but continued to pour in.

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Exhibits

Table 1: Extreme 1-Day Increases in RH Holdings

		Rel Day; Holdings in Thousands						ARH		Stock returns, in %		
Date	Ticker	–2	–1	±0	+1	+2	$\Delta_{-1,0}\#$	w_0	$\Delta_{-1,0}w$	r_{-1}	r_0	r_{+1}
2018/07/26	FB	108	114	156	166	170	42,083	3.22	0.85	0.4	–18.7	–0.1
							Good 2nd-Q earnings, but below expectations, 10% price drop					
2020/01/16	INPX	0	0	26	26	25	26,376	0.27	0.27	–55.5	8.1	–7.2
							1/8: Reverse Stock Split, IOT Sensor Product wins award, Canada Patent.					
2018/10/02	OGEN	17	27	41	39	37	14,336	0.74	0.25	38.8	123.2	–51.1
							Various minor news					
2018/07/17	NFLX	101	107	118	118	117	11,000	2.49	0.23	1.3	–5.6	–1.4
							Poor earnings report, Walmart considers competitive service.					
2019/11/01	FIT	252	252	271	275	275	18,924	3.06	0.21	5.8	14.6	–1.8
							Google agrees to buy Fitbit					
2020/03/06	INO	107	111	137	155	150	25,521	1.16	0.20	25.5	45.5	–22.6
							Accelerated COVID DNA vaccine					
2020/06/03	GNUS	49	66	112	145	141	46,014	0.46	0.19	52.6	95.9	–13.2
							Raised funding for digital children network					
2018/07/27	FB	114	156	166	170	173	9,832	3.40	0.19	–18.7	–0.1	–1.6
							See above for other large increase. Also acquires Redkix.					
2020/06/09	NKLA	33	77	125	130	137	48,019	0.49	0.18	102.5	9.6	–17.9
							Various progress reports. See also below for large decrease 1 week before.					
2020/05/18	SRNE	16	51	92	92	90	41,302	0.41	0.18	157.6	–7.0	–15.6
							Antibody has various positive COVID vaccine news.					

Explanations: These are the ten cases with the largest 1-day ARH investment weight increases. The $\Delta_{-1,0}\#$ column is the exact number of RH holding changes (with subscripts refering to trading days), preceding columns round to thousands. The weight w_0 is the weight of this stock i on day 0, as in the ARH portfolio, $w_{i,t} \equiv N_{i,t} / \sum_i N_{i,t}$, where N_i is the number of RH investors in stock i on day t. The sort column is $\Delta_{-1,0}w$.

Interpretation: There are typically large positive or negative daily rates of return before or around large increases in the number of RH investors.

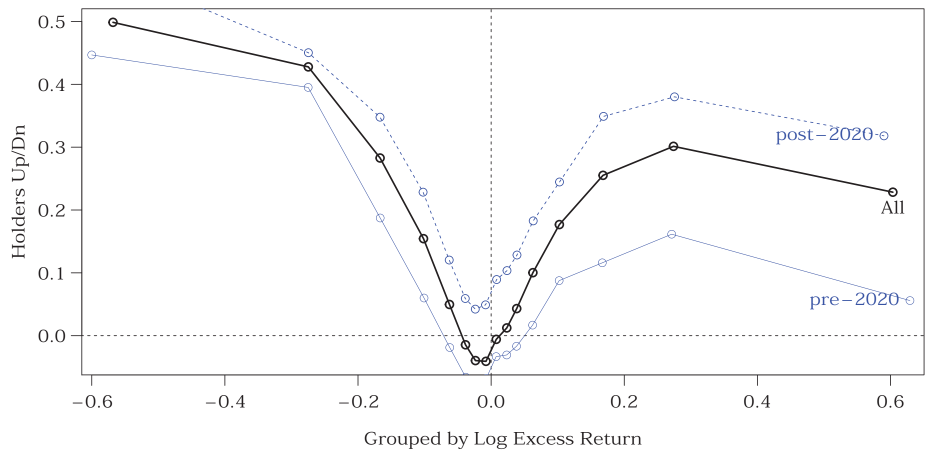
Table 2: Extreme 1-Day Decreases in RH Holdings

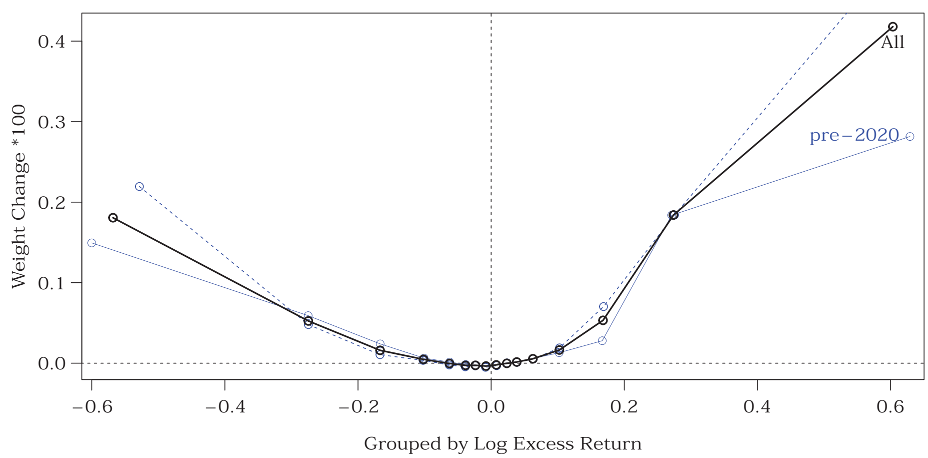
		Rel Day; Holdings in Thousands						ARH		Stock returns, in %		
Date	Ticker	−2	−1	±0	+1	+2	$\Delta_{-1,0}\#$	w_0	$\Delta_{-1,0}w$	r_{-1}	r_0	r_{+1}
2019/02/27	IGC	78	78	42	42	42	−36,084	0.63	−0.71	−2.1	1.9	13.7
Cannabis stock wins appeal to relist on NYSE. Stock rises dramatically. Q3-19 earnings release.												
2018/11/02	INPX	39	40	1	1	1	−38,583	0.03	−0.67	−3.5	−31.5	1.8
Reverse stock split.												
2020/06/04	NKLA	95	100	21	33	77	−78,685	0.09	−0.32	6.9	−0.3	4.0
Various progress reports. see also previous above for large increase 1 week later.												
2020/02/05	TSLA	154	163	148	151	152	−15,339	1.43	−0.15	12.2	−18.3	1.6
Good earnings report. Model-Y news. German factory. Weibo negative report.												
2020/03/13	AIKI	18	18	1	1	1	−17,240	0.01	−0.14	−8.6	−33.8	−12.0
Name change to emphasize Alzheimer and Multiple Sklerosis drug dvlpmt												
2019/02/04	OHRP	8	8	0	0	0	−8,742	0.00	−0.14	−4.6	−23.7	−2.5
Reverse stock split												
2018/10/01	TSLA	95	101	94	94	94	−6,876	1.69	−0.13	−13.9	17.0	−3.1
Musk steps down as chairman and settles with SEC. Next day good earnings news.												
2018/10/04	IGC	89	83	76	72	80	−7,259	1.35	−0.13	−32.0	−26.8	−36.3
10/2: ATM offering completed												
2020/01/16	FIT	257	257	256	257	259	−898	2.59	−0.11	0.6	−0.5	1.0
Scripps Research claims Fitbit can detect flu												
2018/08/02	TSLA	85	85	80	77	76	−4,857	1.61	−0.11	1.0	15.7	−0.9
OK Earnings news. Announces China plan												

Explanations: For more explanations, refer to Table 1. These are the ten cases with the largest 1-day ARH investment weight decreases.

Interpretation: There are sometimes large positive or negative daily rates of return around large decreases in ARH weight. The relation is weaker than it was in Table 1.

Figure 1: RH Holding Changes by Previous Day Net-of-Market Rate of Return





Explanations: Stock–days are first grouped by net-of-market stock returns into about 20 (non-equal-spaced) categories. Within each category, the y-axis presents mean (change) statistics for the full sample (dark) and two subsamples (light, pre-2020 and post-2020) for the subsequent day. The top plot assigns +1 and –1 to stock–days on which the RH number increased and decreased, respectively, and plots the mean over all stock–days in each rate of return bin. The bottom plot shows the net change in the ARH investment weight. This weights a larger number of investor changes more (common in bigger stocks with more RH holders) and also considers other ARH changes on the same day. The sample begins in June 2018 and ends in September 2020.

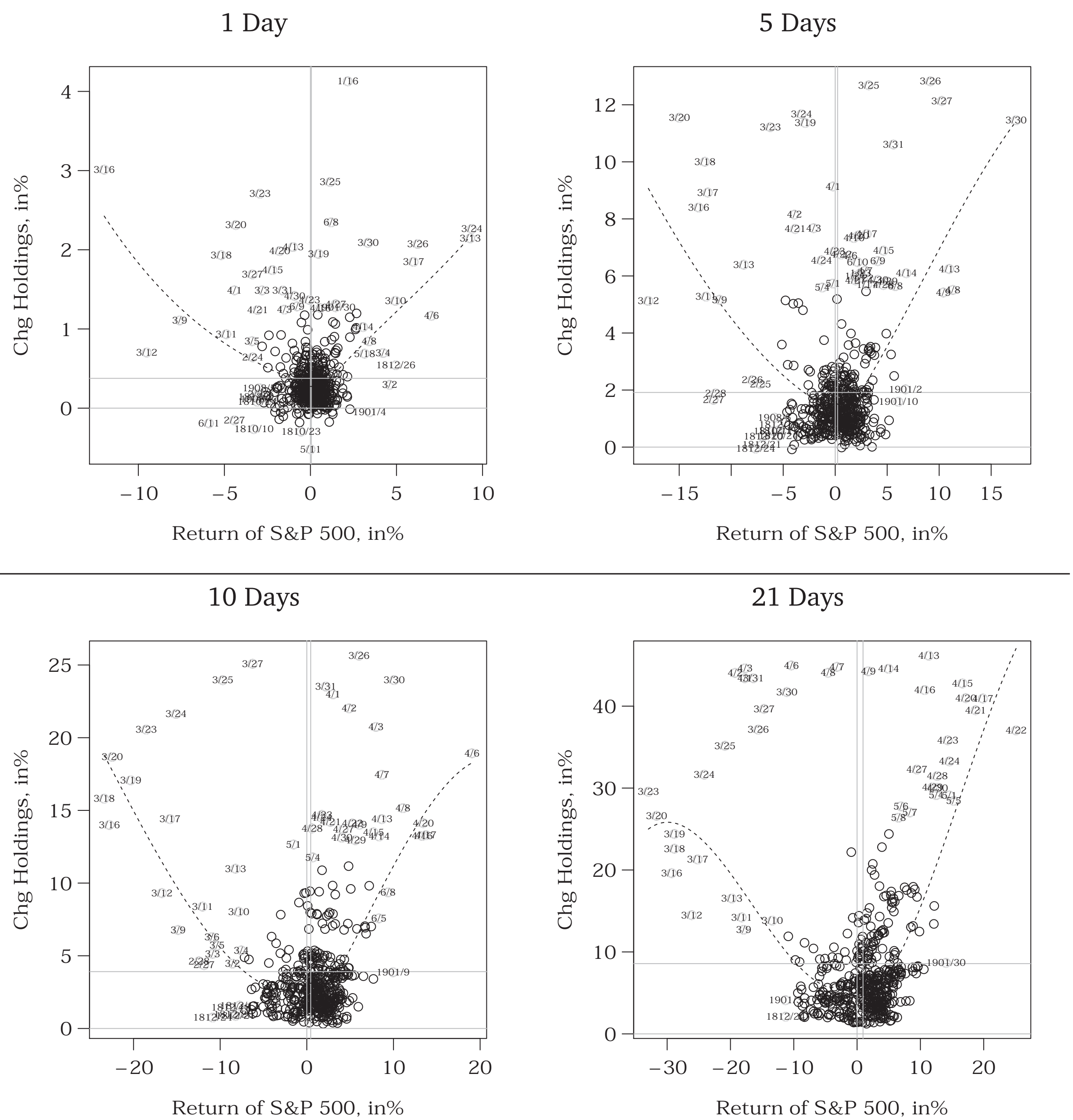
Interpretation: RH investors preferentially purchase large movers. This is similar to the behavior of other retail investors described in earlier work. Contrarian increases are concentrated in small stocks with smaller weight increases relative to the increases in the total number of RH holdings.

Figure 2: Sum Total RH Holdings and Stock Market Performance, 2018-2020

Explanations: The top plot shows the total number of RH investors. The green line shows the public interest in COVID according to Google Trends. The bottom plot shows the S&P 500 index and the percentage change in the sum total of RH holdings. The red line indicates zero growth. (Figure 5 in the appendix is a closeup for 2020.)

Interpretation: RH investing accelerated during the U.S. COVID crisis.

Figure 3: 2018-2020 RH Systematic Contrarianism By Horizon



Explanations: This figure shows the percentage change in the sum-total of RH holdings versus the S&P 500 rate of return, similar to Table 2, but in *x*-*y* rather than in time-series format. The aggregation periods are contemporaneous, equally long for *x* and *y* variables, and overlapping for the longer intervals. Days with large changes are named. The lines are fitted by a local polynomial (loess) regression with a span of 0.75.

Interpretation: Large S&P 500 price drops did not deter RH investors.

Table 3: Daily Percent Changes in the Growth Rate of RH Holdings

	(2018/06/01 to 2020/08/13)				2020/02/03 to 2020/08/13			
	Coef	T	Coef	T	Coef	T	Coef	T
(Intercept)	0.08	2.60	0.03	1.84	0.07	1.77	0.03	0.65
Lagged Values								
lag(Y, 1)	0.52	4.95	0.24	2.69	0.39	4.39	0.30	3.49
lag(Y, 2)			0.26	5.06	0.19	1.84	0.17	1.75
lag(Y, 3)			0.21	3.15	0.16	1.81	−0.07	−0.70
lag(Y, 4)							0.20	2.38
lag(Y, 5)							0.06	0.72
lag(Y, 6)							−0.12	−1.58
Positive Market Movement: $(R_M{>}0) \cdot R_M$								
lagp(R_M, 0)							0.07	2.48
lagp(R_M, 1)	0.13	5.20	0.09	3.09	0.11	2.54	0.13	3.92
lagp(R_M, 2)			0.00	−0.14	−0.03	−0.83	−0.04	−1.47
lagp(R_M, 3)			−0.01	−0.59	−0.02	−0.83	−0.03	−1.14
lagp(R_M, 4)							0.12	4.14
lagp(R_M, 5)							0.03	1.23
lagp(R_M, 6)							0.01	0.19
Positive Market Movement: $(R_M{>}0) \cdot R_M$								
lagn(R_M, 0)							0.00	0.17
lagn(R_M, 1)	0.09	3.99	0.06	3.35	0.08	2.81	0.04	2.13
lagn(R_M, 2)			0.02	1.08	0.01	0.43	−0.02	−0.84
lagn(R_M, 3)			0.00	0.11	−0.00	−0.01	−0.02	−0.89
lagn(R_M, 4)							0.05	2.19
lagn(R_M, 5)							0.02	0.82
lagn(R_M, 6)							−0.01	−0.30
$\bar{R}^2$:	51.6%		59.4%		67.6%		73.4%	
N:	543		541		132		129	

Explanations: The dependent variable Y in this time-series regression is the percentage change in the sum total number of RH holdings, $Y_t \equiv \%\Delta_t \sum_i \mathrm{RH}_{it}$. The market rate of return is the percentage change in the S&P 500. The "positive market movement" variables assign zero to the variable on days when the market declined. The "negative market movement" variables are analogous, except that they use the absolute value of R_M, as indicated in the header, to simplify interpretation. (A positive coefficient means an increase in holdings.) The T-statistics are adjusted for heteroskedasticity and two lags as in Newey and West (1987) (without prewhitening).

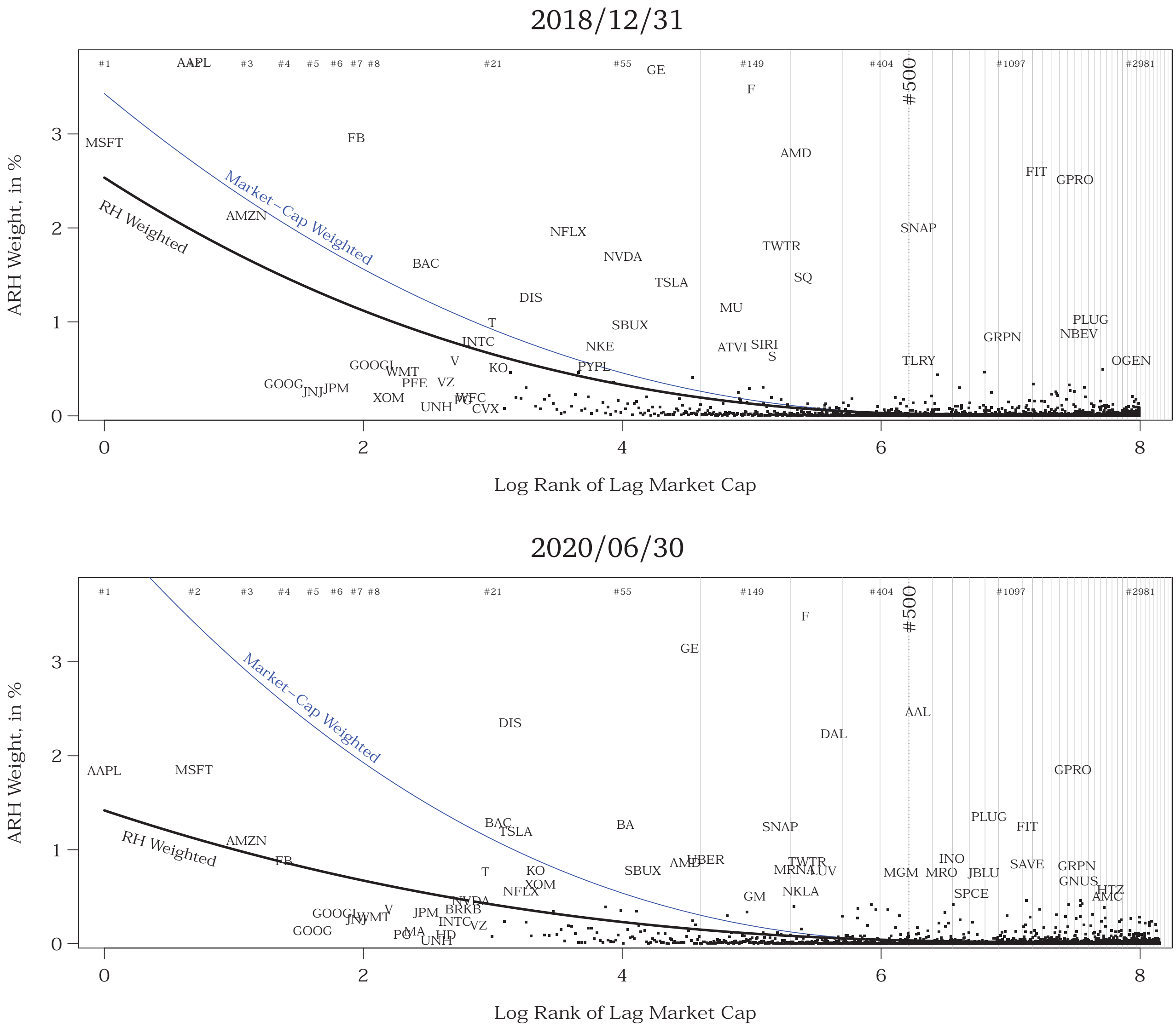
Interpretation: 0-1 day and 4-5 day-lagged large market movements are robust positive predictors of increases in the sum-total number of RH holdings.

Table 4: Highest ARH vs. VWMKT Log-Investment-Rank Differences on 2019/12/31 or 2020/06/30

Year	TIC	Business Description	Rank RH	Rank VW	ARH Pfio Weight
2019	BIOC	Cancer-Detection	102	3356	**0.15**
2019	HUSA	Oil-Gas	88	3425	**0.19**
2019	IGC	India-Cannabis	27	3271	**0.59**
2019	OGEN	BioPharm Immunization	39	3280	**0.47**
2019	RIOT	Blockchain Fin'l	96	3161	**0.17**
2019	ZN	Oil-Gas	95	3296	**0.17**
2020	CEI	Oil-Gas	94	3425	**0.20**
2020	INPX	Big Data	88	3227	**0.22**
2020	OCGN	Eye Disease	101	3403	**0.19**
2020	TTNP	Drug Implants	90	3274	**0.22**

Explanations: RH refers to Robinhood, VW to the value-weighted market (according to CRSP's number of shares times price). The stocks listed in this table (log-)ranked more highly in the investment holdings of RH investors than in the VW market portfolio either on 2019/12/31 or on 2020/06/30, such that they constituted at least 0.15% of the ARH investment weight. (All stocks listed in this table constituted less than 0.005% of the holdings in the VW portfolio.)

Figure 4: Snapshot ARH Weights by Log-Rank of Market Cap



Explanations: Each point is one stock's percentage investment weight in ARH. These weights are plotted against the log market-cap rank (from CRSP). For example, although AAPL was the biggest stock, accounting for 5.2% of the total CRSP market cap on 2020/06/30, it accounted for "only" 1.85% of the ARH portfolio (as marked). For stocks with unusually large ARH investment weights, and for the biggest stocks, the plots show ticker symbols instead of points. The black line fits the (RH) points. For comparison, the blue line shows a smoothed line that a market-cap weighted portfolio would have assigned. Both lines are fitted via loess with a span of 0.75.

Interpretation: Relative to a value-weighted portfolio, RH investors typically underinvested in the biggest 500 stocks, especially in mid-2020. They overinvested in many consumer-related tech stocks, as well as fallen angels (such as Ford (F), General Electric (GE), and United Airlines (UAL)).

Table 5: ARH Investment Weights *Far Above* VWMKT Investment Weights

		Pre-COVID				Post-COVID							
		Dec 2018				Jun2020				Holdings (in K)			Price
		Rank		Weight		Rank		Weight		Dec	Jun		Chg
Tic	Description	ARH	VW	ARH	VW	ARH	VW	ARH	VW	2018	2020	Chg	(RoR)
AAL	American Airlines	114	272	0.12	0.06	3	620	2.39	0.02	7	654	88.7	–0.64
AMD	AMD	6	218	2.70	0.08	21	92	0.84	0.20	161	229	0.4	1.92
BA	Boeing	53	26	0.29	0.78	11	57	1.23	0.34	17	337	18.5	–0.42
DAL	Delta Airlines	82	139	0.17	0.15	5	288	2.16	0.06	10	592	56.1	–0.47
DIS	Disney	17	27	1.22	0.69	4	23	2.28	0.66	72	624	7.6	0.04
F	Ford	3	152	3.35	0.13	1	233	3.38	0.08	200	925	3.6	–0.18
FB	Facebook	4	7	2.85	1.34	19	4	0.86	1.78	170	235	0.4	0.67
FIT	Fitbit	7	1388	2.51	0.00	13	1281	1.21	0.01	149	331	1.2	0.30
GE	General Electric	2	72	3.55	0.28	2	95	3.05	0.20	212	834	2.9	–0.05
GPRO	GoPro	8	1867	2.42	0.00	7	1785	1.79	0.00	144	491	2.4	0.19
INO	Vaccines	384	1931	0.03	0.00	17	725	0.88	0.01	1	241	133.4	5.41
JBLU	JetBlue Airlines	100	587	0.14	0.02	31	920	0.72	0.01	8	197	23.0	–0.36
LUV	Southwest Airlines	51	167	0.29	0.11	27	266	0.75	0.07	17	205	10.8	–0.33
MGM	MGM Casino-Entmt	180	301	0.07	0.05	30	488	0.74	0.03	4	202	44.3	–0.31
MRO	Marathon Oil	129	322	0.10	0.05	29	668	0.74	0.02	6	202	31.6	–0.55
MU	Micron Storage	18	131	1.11	0.15	97	99	0.19	0.19	66	53	–0.2	0.42
NBEV	Cannabis Drinks	24	1927	0.84	0.00	87	2637	0.23	0.00	50	61	0.2	–0.76
NFLX	Netflix	11	37	1.89	0.50	36	25	0.54	0.65	113	148	0.3	0.65
NVDA	Nvidia	13	56	1.63	0.35	42	17	0.44	0.76	97	121	0.2	2.13
PLUG	Hydrogen Fuel	19	2115	0.99	0.00	9	971	1.31	0.01	59	358	5.1	4.85
SAVE	Spirit Airlines	501	689	0.02	0.02	22	1282	0.82	0.01	1	225	174.0	–0.69
SNAP	Snapchat	10	559	1.93	0.02	14	189	1.21	0.09	115	330	1.9	2.66
SQ	Square Pymnts	15	230	1.41	0.07	61	145	0.33	0.12	84	89	0.1	0.68
TSLA	Tesla	16	82	1.37	0.24	15	24	1.16	0.65	81	317	2.9	1.73
TWTR	Twitter	12	194	1.74	0.09	20	236	0.84	0.08	104	231	1.2	–0.03
UAL	United Airlines	335	188	0.04	0.10	12	437	1.23	0.03	2	336	157.2	–0.60
XXII	Cannabis-Nctn	23	2050	0.85	0.00	103	2793	0.19	0.00	51	51	0.0	–0.67
ZNGA	Gaming (FB)	21	757	0.94	0.01	23	464	0.77	0.03	55	210	2.8	1.14
									All ARH:	5,973	27,390	3.6	0.24

Explanations: These are the companies with the largest (absolute) excess ARH weights over the value-weighted market cap (VWM) weights either on 2018/12/31 or 2020/06/30. The holdings changes and rates of return in the last four columns are from 2018/12/31 to 2020/06/30.

Interpretation: Some companies increased their ARH minus VW weights through active RH purchases, some due to less purchasing of other stocks, and some due to price drops affecting the VW weight.

Table 6: Correlations of QRH with ARH

Panel A: Correlations of Portfolio Investment Weights

		w(VOL)	w(DOLVOL)	w(QRH)
w(ARH)	on 2018/12/31	0.73	0.67	0.81
w(ARH)	on 2019/12/31	0.67	0.54	0.71
w(ARH)	Pooled XS and TS	0.71	0.43	0.76

Panel B: Correlations of Daily Portfolio Returns in the Time Series

Portfolio	Return Adjustment	Correlation
QRH	Raw	0.98
	Net of 1-F Model	0.87
	Net of 6-F Model	0.78
–20190631	Net of 6-F Model	0.80
20190631–	⋮	0.79
QRH	Net of 1×Market	0.88
SMB	⋮	0.05
HML	⋮	–0.05
RMW	⋮	0.25
CMA	⋮	–0.29
UMD	⋮	–0.48

Explanations: The QRH portfolio is 2/3 of a 1-year volume-weighted portfolio (VOL) and 1/3 of a 1-year dollar volume-weighted portfolio (DOLVOL). These two variables and weights were roughly chosen based on an empirical exploration of many variables predicting ARH investment weights. The two QRH input variables are themselves correlated, and reasonable alternative weightings do not greatly change the return correlations.

Interpretation: The QRH portfolio is an (albeit imperfect) proxy for the ARH portfolio.

Table 7: Return Performance of the ARH Crowd Portfolio

Panel A: Daily Rebalancing / Returns

No Delay	0-F	1-F	6-F
alpha	0.104	0.050	0.065
(T)	(1.27)	(1.37)	(2.70)
XMKT		1.13	1.03
SMB			0.45
HML			–0.10
RMW			–0.21
CMA			–0.57
UMD			–0.35
546 Days (2018/06/01 – 2020/08/14)			

5-Day Delay	0-F	1-F	6-F
alpha	0.097	0.045	0.062
(T)	(1.19)	(1.28)	(2.63)
XMKT		1.13	1.04
SMB			0.44
HML			–0.11
RMW			–0.22
CMA			–0.55
UMD			–0.34
546 Days (2018/06/07 – 2020/08/20)			

Panel B: Monthly Rebalancing / Returns

No Delay	0-F	1-F	6-F
alpha	2.09	0.61	1.29
(T)	(1.46)	(1.13)	(2.46)
XMKT		1.30	1.09
SMB			0.89
HML			–0.36
RMW			–0.47
CMA			0.09
UMD			–0.19
27 months (2018/06 – 2020/08)			

3-Month Delay	0-F	1-F	6-F
alpha	1.92	0.75	1.20
(T)	(1.20)	(1.38)	(2.43)
XMKT		1.30	1.13
SMB			0.74
HML			–0.31
RMW			–0.30
CMA			0.04
UMD			–0.15
26 months (2018/08 – 2020/09)			

Panel C: Annual Mid-Year Rebalancing / Returns (Not Regression Coefficients)

	ARH	XMKT	SMB	HML	RMW	CMA	UMD	RF
2018/07 - 2019/06	8.2	8.0	–13.1	–11.8	4.9	–1.5	–0.5	2.2
2019/07 - 2020/06	26.5	8.8	–9.5	–33.2	0.5	–5.6	7.1	1.3

Explanations: The ARH portfolio weights are based on the number of RH investors in each stock, as in Equation 1 ($w_i \equiv N_i / \sum N_i$). The table shows the (net-of-riskfree) return performance of the ARH portfolio with respect to various rebalancing intervals, delays, and benchmarks. The 0-F benchmark is the mean (net of the prevailing risk-free rate). The 1-F benchmark is the CAPM. The 6-F benchmark is the Fama–French 5-factor model plus momentum. T-statistics are Newey–West adjusted (1 lag, no pre-whitening).

Interpretation: The ARH crowd portfolio did not underperform. Rebalanced daily, it tilted towards small (SMB) aggressive (CMA) past-loser (UMD) stocks.

Table 8: Return Performance of the QRH Proxy Portfolio

Panel A: Daily Rebalancing / Returns

No Delay	0-F	1-F	6-F
alpha	0.059	0.005	0.029
(T)	(0.79)	(0.19)	(2.00)
XMKT		1.14	1.05
SMB			0.35
HML			0.06
RMW			–0.20
CMA			–0.24
UMD			–0.21
546 days (2018/06/01 - 2020/08/14)			

5-Day Delay	0-F	1-F	6-F
alpha	0.052	0.000	0.027
(T)	(0.69)	(0.02)	(1.87)
XMKT		1.14	1.06
SMB			0.35
HML			0.06
RMW			–0.20
CMA			–0.24
UMD			–0.21
546 days (2018/06/07 - 2020/08/20)			

Panel B: Monthly Rebalancing / Returns

3-Month Delay	0-F	1-F	6-F
alpha	1.08	–0.45	0.40
(T)	(0.74)	(–1.65)	(1.37)
XMKT		1.35	1.21
SMB			0.56
HML			–0.05
RMW			–0.33
CMA			0.26
UMD			–0.10
27 Months (2018/06 to 2020/08)			

3-Month Delay	0-F	1-F	6-F
alpha	0.86	–0.35	0.36
(T)	(0.56)	(–1.45)	(1.52)
XMKT		1.34	1.21
SMB			0.49
HML			–0.04
RMW			–0.24
CMA			0.19
UMD			–0.11
26 Months (2018/08 to 2020/09)			

Panel C: Including a QRH Volume Factor Component in ARH Return Regression, 27 months

	alpha	(T)	XMKT	SMB	HML	RMW	CMA	UMD	QRH
(I)	1.29	(2.46)	1.09	0.89	–0.36	–0.47	0.09	–0.19	
(II)	0.67	(1.74)	–0.24	0.27	–0.32	–0.08	–0.18	–0.07	1.11

Explanations: Panels A and B are analogous to Table 7 with QRH excess return as the dependent variable instead of the ARH excess return. QRH is 2/3 a number-of-shares trading volume variable (mapped into a weight as in $w_i(v_i) \equiv v_i / \sum_i v_i$) and 1/3 a dollar trading volume variable ($w_i(d_i) \equiv d_i / \sum_i d_i$). Panel C explores the QRH portfolio return as an independent factor explaining the ARH rate of return.

Interpretation: QRH is not as good a predictor of future returns as ARH. The volume component in QRH can account for about half of the ARH alpha.

Table 9: Extended Return Performance of the QRH Proxy Portfolio After 1980

No Delay Monthly Returns	0-F	1-F	6-F
alpha	0.60	–0.32	0.16
(T)	(1.96)	(–2.99)	(1.86)
XMKT		1.34	1.17
SMB			0.33
HML			–0.10
RMW			–0.44
CMA			–0.20
UMD			–0.24
489 months (1980/01 - 2020/09)			

November Investment Weights Annual Returns	0-F	1-F	6-F
alpha	8.0	–3.1	0.3
(T)	(2.59)	(–2.90)	(0.40)
XMKT		1.26	1.10
SMB			0.47
HML			–0.13
RMW			–0.44
CMA			0.00
40 years (1980-2019)			

Explanations: The dependent variable is the rate of return on the QRH portfolio net of the risk-free rate (as used and described in the two previous tables). QRH is a 2/3 the 1-year volume-trading and 1/3 the 1-year dollar-volume trading portfolio. Annual returns are for calendar years, with weights chosen in November of the preceding year.

Interpretation: Over a 40-year interval, the QRH portfolio performed about the same as it performed in the 2018-2020 sample.

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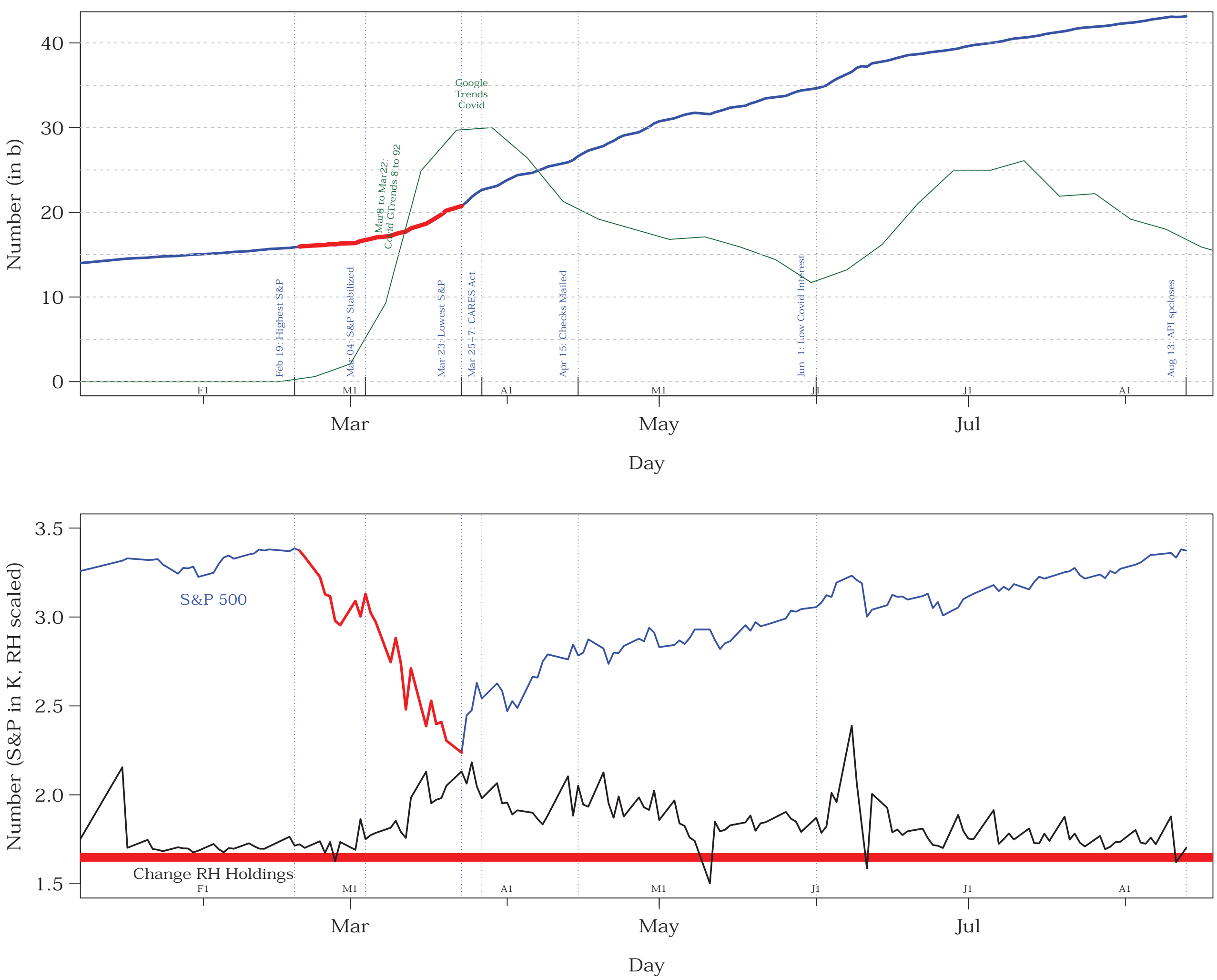
Figure 5: Sum-Total RH Holdings and Stock Market Performance in 2020



Explanations: This figure is a closeup of Figure 2.

Interpretation: The COVID-related drop in the stock market coincided with an acceleration of sum-total RH positions.

Table 10: Appendix: Equivalent Correlations in the Barber–Odean 1991-1995 Data

Panel A: 20,939 Year-End Portfolio Investment Weights Correlations

		Households	
	QBO	HH-VW	HH-EW
ABO	0.75	0.78	**0.97**
ABOxP	0.43	0.34	0.57

Panel B: 20,939 Year-End ARH-Equivalent ABO Portfolio Investment Weight Correlations

	ABO	ABOxP	HH-VW	HH-EW
QBO	**0.75**	0.43	0.60	0.72

Panel C: Portfolio Return Correlations over 59 Months

Raw Returns							
	With BO Info		BO Household		Aggregate		
	QBO	ABOxP	HH-VW	HH-EW	EWM	VWM	RF
ABO	0.96	0.85	0.93	0.99	0.84	0.91	0.20
QBO		0.91	0.83	0.98	0.89	0.84	0.22
Both Returns Net of VW Market Return							
	With BO Info		BO Household		Aggregate		
	QBO	ABOxP	HH-VW	HH-EW	EWM	VWM	RF
ABO	**0.86**	0.33	**0.98**	**0.99**	0.86		–0.11
QBO		0.39	0.80	0.81	0.67		–0.35

Explanations: The table shows portfolio weight and return correlations in the Barber–Odean data for 304,929 unique end-of-month holdings from 1991 to 1996 (equities only). The "ABO" portfolio is based only on the number of Barber–Odean investors in each stock (on a given month-end) and equivalent to the ARH portfolio. QBO is the rolling 12-month volume and dollar volume-based portfolio, equivalent to QRH. The "ABOxP" is like the ABO portfolio, except it first multiplies the number of investors in each stock by the stock price. The **HH-VW** portfolio simply adds up the dollar investment amounts over all investors. The **HH-EW** first normalizes each household to $1 before adding up. The most interesting correlations and are boldfaced.

Interpretation: (1, Panel A) The ABO portfolio is similar to an equal-weighted portfolio of Barber–Odean households. (2, Panels B&C) The predictive properties of the QBO portfolio for the ABO portfolio are similar to the predictive properties of the QRH portfolio for the ARH portfolio.